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Multi-Objective Optimization of Liquid-Cooled Serpentine Cooling Plate for Battery Packs Based on Multi-Feature Parameters and Machine Learning#

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ABSTRACT

With the superior heat transfer coefficient and operational stability, liquid cooling has become the most prevalent technology in battery thermal management systems. Traditional designs of serpentine cooling plates are often developed through trial-and-error adjustments to parameters such as plate width and channel length, relying heavily on engineering experience. These designs typically halt iteration once basic technical requirements are satisfied, rather than striving to maximize heat transfer performance, thereby constraining the cooling potential of serpentine plates. This study introduces a machine learning-driven strategy within a physics-based framework that integrates heat transfer and fluid dynamics equations to optimize serpentine cooling plates for high heat generation scenarios. Leveraging the NSGA II algorithm, the framework optimizes critical design parameters while elucidating their influence on key physical characteristics during the design process. At a heat generation rate of 6 kW, the cooling plate—validated through experimental simulations—achieves a maximum temperature difference of 8.5°C in the battery cell region, showcasing outstanding heat transfer performance. Compared to conventional serpentine cooling plates, it enhances temperature uniformity by 30% at an equivalent pressure drop.

Keywords: battery thermal management, liquid-cooled plate, machine learning, physics-informed machine learning, multi-objective optimization

NONMENCLATURE

Abbreviations	
BTMS	Battery Thermal Management Systems
ML	Machine learning
ANNs	Artificial Neural Networks
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PIML	Physics-Informed Machine Learning
CFD	Computational Fluid Dynamics
RSM	Response Surface Methodology
Symbols	
v	Velocity
q	Volumetric Flow Rate
A	Cross-sectional Area
ΔP	Pressure Drop
ΔT_{max}	Maximum Temperature Differential
D_h	Equivalent diameter
Q	Heat Transfer Capacity
h	Heat Transfer Coefficient
A_h	Effective Surface Area
Pr	Prandtl Number
Re	Renolds Number
λ	Thermal Conductivity

1. INTRODUCTION

Liquid cooling for batteries, due to its high heat transfer coefficient and operational stability, is the most widely applied thermal management solution in the battery domain and has already been extensively implemented in the automotive industry[1]. As the primary thermal interface with batteries, cold plates critically influence thermal management. While conventional serpentine designs offer structural simplicity and reliable cooling, their inherent high pressure drop persists despite prevalent channel optimization efforts to improve thermal performance[2]. Common optimization parameters for cold plates include the channel width, depth, height, and the number and arrangement of channels. For instance, increasing channel width can reduce battery temperature but leads to higher pressure loss, requiring a trade-off between conflicting performance metrics[3]. Parameters such as

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the number of channels and their symmetrical or staggered arrangements also influence temperature uniformity and cooling efficiency[4].Structurally, the design of serpentine cold plates is typically determined empirically, followed by parameter optimization to enhance performance. However, the optimization potential of the structure itself is limited[5].Conventional optimization relies on trial-and-error geometric adjustments, which are time-consuming and often fail to achieve optimal thermal performance. Unlike traditional mathematical modeling approaches, machine learning offers a more effective solution for addressing the complex thermodynamics and temperature distribution challenges in battery thermal management. By uncovering nonlinear relationships and patterns difficult to detect with conventional methods[6].

Machine learning offers diverse algorithms for battery system modeling, optimization, and control. Particularly effective for small datasets or simple structures, ML enables efficient modeling with minimal computational resources. For systems with limited parameters and straightforward input-output relationships, these methods provide easier implementation, simpler tuning, and reduced hyperparameter sensitivity compared to conventional approaches[7]. Artificial Neural Networks (ANNs) enable precise identification of thermal gradients in battery packs (hotspots/cold spots), directly informing cold plate optimization[8]. Tang also utilized ANNs models to optimize structural parameters of microchannel cold plates, achieving high-precision battery temperature predictions[9]. Interpretable algorithms (linear regression, decision trees) further elucidate parameter-performance relationships, providing actionable insights for cooling system refinement[10]. A two-step surrogate model approach can replace the mapping between input variables and system responses, optimizing performance metrics such as maximum temperature and pressure drop[11]. Kriging models, in particular, have demonstrated higher goodness-of-fit (R^2) in various cases and, when combined with NSGA-II algorithms, have enabled multi-objective optimization of cold plate structures[12]. Zhong et al.[13] used NSGA-II to optimize average temperature and temperature uniformity, with both experiments and simulations validating the optimization effectiveness of tree-shaped cold plates.

In addition to machine learning approaches, deep learning has also been employed by researchers to optimize cold plates and battery packs. Guo et al.[14] combined CFD simulations with neural network predictions to optimize structural parameters such as the number of channels, dimensions, and flow rates of cold plates, resulting in an optimal cold plate design scheme. Ebbs-Picken et al.[15]developed a hierarchical thermal modeling framework integrating deep encoder-decoder neural networks for high-fidelity physical field prediction with surrogate-model-assisted channel optimization. The methodology incorporates manufacturability constraints to generate production-feasible, application-specific cold plate designs for advanced battery thermal management systems. Zheng et al.[16].developed a thermal model for pouch-type lithium-ion batteries under natural cooling conditions, using a five-layer ANNs to predict temperature extremes and pressure drop. NSGA-II optimization of cold plate parameters effectively reduced maximum temperature and thermal variations.

Machine learning is particularly advantageous for cold plate optimization under parameter constraints and limited data, offering computational efficiency and interpretability. Sui [17] demonstrated this through a genetic algorithm-based response surface method, achieving 95% computational cost reduction. Traditional geometric optimization methods often suffer from restricted design freedom and local optima traps[18]. While purely data-driven ML shows promise in related fields, its applications face interpretability and generalization challenges. Physics-Informed Machine Learning (PIML) addresses these limitations by integrating physical principles, enhancing model accuracy and engineering relevance - an approach equally valuable for cold plate optimization[19].

2. MATERIAL AND METHODS

2.1 Simulation model

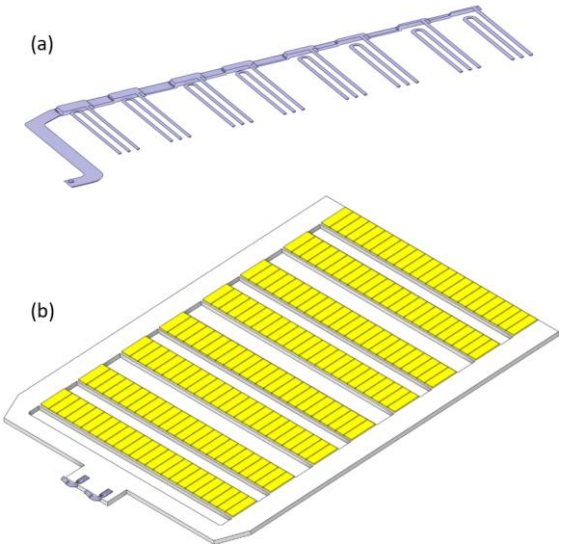

Fig. 1 (a)The structure of plate channel; (b)Numerical Model Configuration and Cold Plate Architecture

The longitudinal cross-sectional schematic of the cooling plate reveals a primary U-shaped manifold with eight branching channels, where the manifold exhibits a stepwise diameter reduction profile, and each semi-manifold segment comprises three interconnected S-configured conduits. The numerical simulation employs the following boundary conditions: a total fluid mass flow rate of 10.32 L/min, constant inlet temperature of 15°C, and uniform heating power of 6 kW. The computational domain comprises the cooling plate, thermal conductive grease layer, and heating film assembly, forming a fully coupled thermal-fluid system.

2.2 Mathematical model

The computational framework incorporates fundamental physical equations including：

The input parameters primarily consist of the pipe cross-sectional area (*A*) , while the objective functions for optimization include minimizing both the maximum temperature differential (ΔT_{max}) cross the cooling plate and the pressure drop (ΔP) . The computational procedure initiates by deriving the flow velocity and equivalent diameter (D_h) through fundamental hydraulic relationships involving the volumetric flow rate and cross-sectional area.

$$v = \frac{q}{A} \tag{1}$$

$$D_h = 2\sqrt{\frac{A}{pi}} \tag{2}$$

In the Eq.2, pi represents the wetted perimeter of the pipe. The total flow resistance comprises frictional losses (Darcy-Weisbach) and localized losses, with the cold plate's predominant localized resistance originating from abrupt sectional transitions and tee-junction configurations.

$$\Delta Ptotal = \Delta Pfriction + \Delta Plocal \tag{3}$$

$$\Delta Pfriction = f \cdot \frac{L}{D_h} \cdot \frac{\rho v^2}{2} \tag{4}$$

$$\Delta Plocal = \frac{(K \cdot \rho v^2)}{2} \tag{5}$$

In Eq. 4, L represents the characteristic length of the flow channel. In Eq. 5, K represents the local resistance loss coefficient.

The thermal modeling framework focuses exclusively on convective heat transfer mechanisms at the cooling plate interface, where solid-fluid thermal interactions are characterized by the product of the convective heat transfer coefficient (*h*) and effective surface area (A_h) . Notably, conductive heat transfer through solid components is excluded from the present analysis.

$$Q = h \cdot A_h \cdot \Delta T \tag{6}$$

The value of the convective heat transfer coefficient is calculated using the following two formulas, corresponding to different Reynolds number conditions. First is the laminar flow region. When pipe flow with Reynolds numbers below 2300, the Zied-Tate formula is applied.

$$Nu = 0.186\left(\mathrm{RePr}\frac{D_h}{L}\right)_f^{\frac{1}{3}}\left(\frac{\mu_f}{\mu_w}\right)^{0.14} \tag{7}$$

μ_f and μ_w represent the dynamic viscosity at bulk fluid temperature and wall temperature, respectively. *Re* denotes the Reynolds number, *Pr* the Prandtl number.

For the flowing medium, a water-ethylene glycol solution, Pr is calculated as follows:

$$Pr = \frac{\mu \cdot Cp}{\lambda} = \frac{4.305 \cdot 3455.5}{0.42} = 35.42 \tag{8}$$

The Nusselt number(Nu) in the transition regime is calculated using the following formula:

$$Nu = 0.012(\mathrm{Re}^{0.87} - 280)Pr^{0.4}\left[1 + \left(\frac{\mathrm{D_h}}{\mathrm{L}}\right)^{\frac{2}{3}}\right]\left(\frac{Pr_f}{Pr_w}\right)^{0.11} \tag{9}$$

After obtaining the Nu for the pipe segment, the formula for calculating the convective heat transfer coefficient is as follows:

$$h = \frac{Nu \cdot \lambda}{D_h} \tag{10}$$

where λ is the thermal conductivity of the fluid (water-glycol solution).

The foregoing equations are integrated with response surface methodology (RSM) and the NSGA-II to implement machine learning-driven optimization of flow channel cross-sectional areas.

3. RESULTS

The temperature distributions between the initial and machine learning-optimized serpentine cold plates reveals significant thermal performance improvements, with a 4.4°C reduction in maximum temperature and a decrease in the heating film's maximum temperature differential from 12.2°C to 8.5°C, demonstrating the effectiveness of the optimization approach.

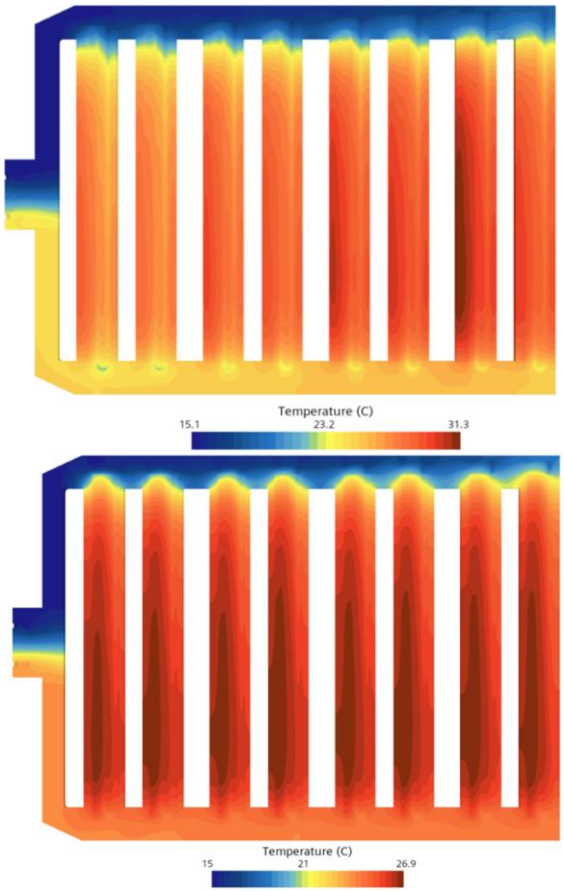

Fig. 2 The temperature distributions between the initial and machine learning-optimized serpentine cold plate

The comparative analysis of temperature and pressure drop contour plots reveals that both the baseline and machine learning-optimized cold plates exhibit similar overall thermal distributions due to their fundamentally conserved structural configurations. However, while the baseline design demonstrates localized high-temperature zones in Pipe Section 7, the ML-optimized configuration achieves superior thermal uniformity across all eight pipe sections. This improvement stems from the optimized flow distribution characteristics, where the ML algorithm deliberately establishes a progressively increasing flow rate relationship among the branch pipes. This design rationale accounts for the inherent temperature rise along the main manifold, where downstream branches naturally require greater coolant flow to compensate for the accumulated thermal load, rather than pursuing an idealized equal-flow distribution. The resultant flow allocation strategy effectively balances temperature uniformity with hydraulic efficiency.

4. DISCUSSION

For serpentine cold plates, the primary objective is to achieve an appropriate flow distribution across all branch segments to ensure uniform thermal performance and efficient cooling. The flow distribution is influenced by the cross-sectional area of the channels; however, it is more directly determined by the relative sizes of the branch segments. Specifically, the flow rate in each branch segment is proportional to its relative cross-sectional area, with larger relative areas (as a percentage of the total A facilitating higher flow rates. This relationship between flow rate and relative size plays a critical role in designing cold plates that meet specific cooling requirements.

Once the desired flow distribution is achieved to satisfy practical application demands—ensuring that the flow rates in each segment align with the thermal management objectives—it becomes imperative to address the turbulence characteristics within the flow channels. Turbulence is crucial for enhancing convective heat transfer performance, as it increases the Reynolds number and thereby improves the heat transfer coefficient. In this study, turbulence is primarily modulated through adjustments to the A, which not only strengthens internal flow mixing but also promotes more effective thermal exchange. This approach highlights the interplay between flow distribution, channel geometry, and heat transfer efficiency, offering a pathway for optimizing the design of serpentine cold plates for advanced thermal management applications.

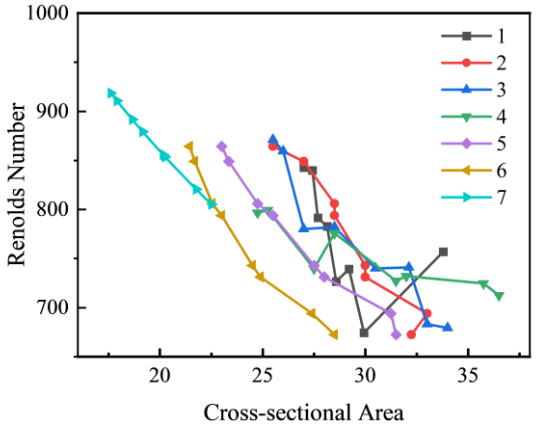

Fig. 3 The Reynolds Number of Characteristic Cold Plate

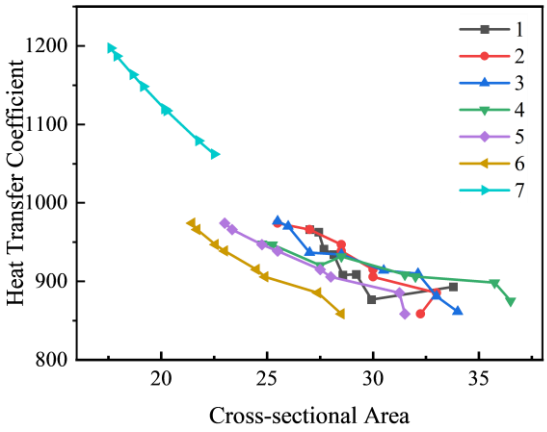

Fig. 4 The h of Characteristic Cold Plate A

As observed from the graph, the Reynolds number and the heat transfer coefficient are strongly correlated with the cross-sectional area of the channels. Specifically, smaller cross-sectional areas result in higher Reynolds numbers and significantly increased heat transfer coefficients. Notably, the increase in the heat transfer coefficient is more pronounced than that of the Reynolds number. Furthermore, when the cross-sectional area is reduced below a certain threshold, the heat transfer coefficient exhibits a distinct stepwise enhancement.

For the maximum temperature of the entire serpentine cold plate, it decreases consistently as the overall cross-sectional area becomes smaller, though it approaches an upper limit. The relationship between the maximum temperature, the heat transfer coefficient, and the maximum temperature difference, which is a key component of the objective function, is more complex. This complexity arises because heat transfer depends on the interaction between the heat transfer coefficient, the heat transfer area, and the temperature difference:

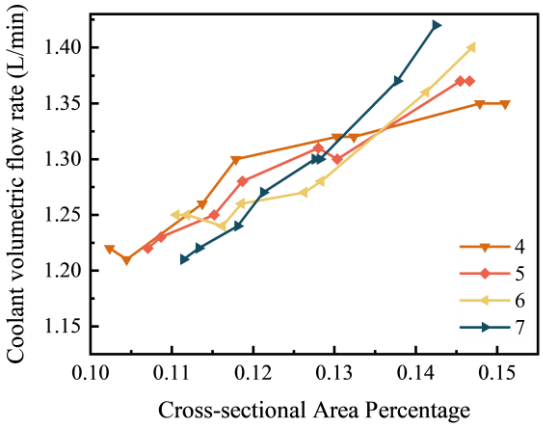

Fig. 2 The q of Characteristic Cold Plate A percentage

When the cross-sectional area of a channel is reduced, the heat transfer coefficient tends to increase. However, this reduction also leads to a decrease in the heat transfer area. As a result, there exists an optimal heat transfer coefficient that minimizes both the maximum temperature and the maximum temperature difference. It is also important to note that, under steady-state conditions, the total heat transfer remains constant. Consequently, ΔT is directly influenced by the interplay between h and A_h.

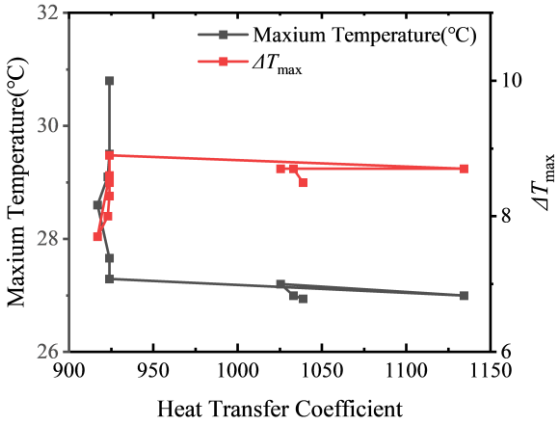

Fig. 6 Relationship Between Thermal Performance Metrics and h

Additionally, due to the similarity of boundary layers, the intensity of heat transfer is closely linked to the flow intensity. Therefore, achieving optimal performance for the serpentine cold plate requires multi-objective optimization of the cross-sectional areas of the main and branch channels, particularly under acceptable pressure loss constraints. By leveraging machine learning techniques for such multi-objective optimization, it is possible to enhance the overall thermal performance of the cold plate system, balancing factors such as heat transfer coefficient, pressure drop, and temperature uniformity.

5. CONCLUSIONS

Liquid cooling has become the dominant technology in battery thermal management systems due to its superior heat transfer performance and operational stability. However, traditional serpentine cooling plate designs rely on trial-and-error methods, often focusing only on meeting basic technical requirements rather than achieving optimal performance. To address this limitation, this study introduces a machine learning-driven optimization strategy within a physics-based framework that couples heat transfer and fluid dynamics equations. By leveraging the NSGA II algorithm, the framework optimizes key design parameters and delivers significant improvements in heat transfer performance and temperature uniformity.

Key findings of this study are as follows:

(1) Traditional designs are constrained by reliance on engineering experience and lack rigorous optimization, often stopping at satisfactory performance rather than maximizing cooling potential.

(2) At a heat generation rate of 6 kW, the optimized cooling plate achieves a maximum temperature difference of 8.5°C in the battery cell region. This represents a 30% improvement in temperature uniformity compared to conventional designs, under equivalent pressure drop conditions.

(3) The machine learning-driven framework enables a systematic and efficient optimization process, providing insights into the relationship between design parameters and thermal performance. This approach paves the way for more efficient, reliable, and high-performance cooling solutions in demanding thermal management applications.

(4) The maximum temperature and minimum temperature difference of cold plates are determined by both the heat transfer coefficient and effective surface area, which have competing effects. Physics-constrained machine learning effectively optimizes this trade-off through quantitative sensitivity analysis, achieving balanced thermal-hydraulic performance.

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