



REVIEW

A Comprehensive Review on the Design of Liquid Cooling Plates in Battery Thermal Management

Zerui Chen, Yixuan Zeng, Tengge Mi and Xiaomin Kang*

School of Mechanical Engineering, University of South China, Hengyang, China

*Corresponding Author: Xiaomin Kang. Email: kxm@usc.edu.cn

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ABSTRACT: Lithium-ion batteries are sensitive to operating temperature, making the Battery thermal management system (BTMS) a critical technical bottleneck in electric vehicle development. The liquid cooling plate is the core heat-exchange component in liquid cooling systems, and its optimized design directly sets the performance ceiling of BTMS. Unlike previous reviews that focused on single cooling methods or general BTMS performance, this review specifically addresses liquid cooling plate (LCP) channel design and optimization for prismatic/pouch lithium-ion batteries under water/glycol-based single-phase cooling, based on a systematic literature screening (2015–2026). This review systematically examines recent advances in channel structure innovations and multi-objective optimization methods for liquid cooling plates. It aims to clarify the current technical trajectory and identify key knowledge gaps. This review is structured as follows: traditional channel configurations, bionic and fractal designs, and topology-optimized channel generation. The review reveals an evolutionary pattern from regular geometries to bio-inspired forms and finally to free-form topologies. Beyond tracking this structural evolution, we further critically synthesize how surrogate-model-assisted multi-objective optimization frameworks resolve the inherent conflicts between heat dissipation and energy consumption. These optimization frameworks are examined with particular attention to their trade-off mechanisms, accuracy of surrogate models, and practical constraints including manufacturability and experimental validation. Furthermore, it indicates that bionic channels (e.g., vein networks and spider webs) and topology-optimized channels generally outperform traditional designs in temperature uniformity and flow resistance. Moreover, surrogate model-assisted optimization frameworks can significantly reduce computational costs in multi-objective problems. However, existing studies share several common challenges: numerical simulations dominate while experimental validation is insufficient; optimization conclusions often lack generality across different operating conditions; complex channel designs are not easily integrated with engineering manufacturing; and full-life-cycle factors such as battery aging are rarely considered in optimization. Future efforts should focus on intelligent surrogate models with real-time control, system-level coordination with vehicle thermal management, and performance evaluation over the entire life cycle. Multidisciplinary integration is expected to be the key driving force for sustained breakthroughs in this field.

KEYWORDS: Liquid cooling plate; battery thermal management system; structural optimization; topology optimization; multi-objective optimization

1 Introduction

The global energy crisis and worsening environmental pollution have accelerated the transition toward renewable energy and clean transportation worldwide [1–3]. The transportation sector, as a major source of fossil fuel consumption and greenhouse gas emissions, urgently needs a green transformation through

electrification [4]. In this context, electric vehicles (EVs) have become the mainstream direction of the automotive industry, owing to their zero emissions and low operating costs. Lithium-ion batteries (LIBs) are the most critical power storage components in EVs, due to their high energy density, long cycle life, and low self-discharge rate [5–7].

However, LIBs are highly sensitive to operating temperature. Their performance, lifespan, and safety depend strongly on temperature control [8,9]. Studies show that the optimal operating temperature range for LIBs is typically 15–40°C, and the temperature difference within a battery module should be kept within 5°C. Outside this range, high temperatures accelerate capacity fading, increase internal resistance, and may trigger thermal runaway. Low temperatures, on the other hand, raise electrolyte viscosity, induce lithium plating, and cause sudden power drops. Therefore, a reliable Battery Thermal Management System (BTMS) is a necessary prerequisite for safe and efficient LIB operation.

Currently, mainstream BTMS technologies include air cooling, liquid cooling, phase change material (PCM) cooling, and heat pipe cooling. Air cooling is simple and low-cost, but the low specific heat and thermal conductivity of air make it difficult to meet the heat dissipation demands of high-energy-density batteries under high-rate charge/discharge cycles [10]. PCM cooling absorbs heat through latent heat of phase change, offering good temperature uniformity and no extra energy consumption. However, its low thermal conductivity leads to complete melting and failure under continuous high-rate conditions [11–13]. Heat pipes have extremely high equivalent thermal conductivity, but their contact area is limited, and the system is relatively complex [14,15]. In contrast, liquid cooling technology, thanks to the much higher specific heat and thermal conductivity of coolants, achieves superior heat dissipation efficiency and temperature uniformity. It has become the dominant thermal management solution for high-power, high-energy-density battery modules. Some studies indicate that the cooling efficiency of liquid-based BTMS can be 3500 times that of air cooling, saving up to 40% of energy consumption [1]. Production models such as Tesla Model S/X/3, Chevrolet Volt/Bolt, and BMW i3 all use liquid-cooled BTMS, fully validating its engineering feasibility and reliability [7].

Fig. 1 schematically outlines the technical progression of LCP design covered in this review, tracing the evolutionary path from conventional channel configurations through bionic/fractal structures to topology-optimized channel generation. The key features, advantages, and limitations of the four mainstream cooling technologies are summarized and compared in Table 1.

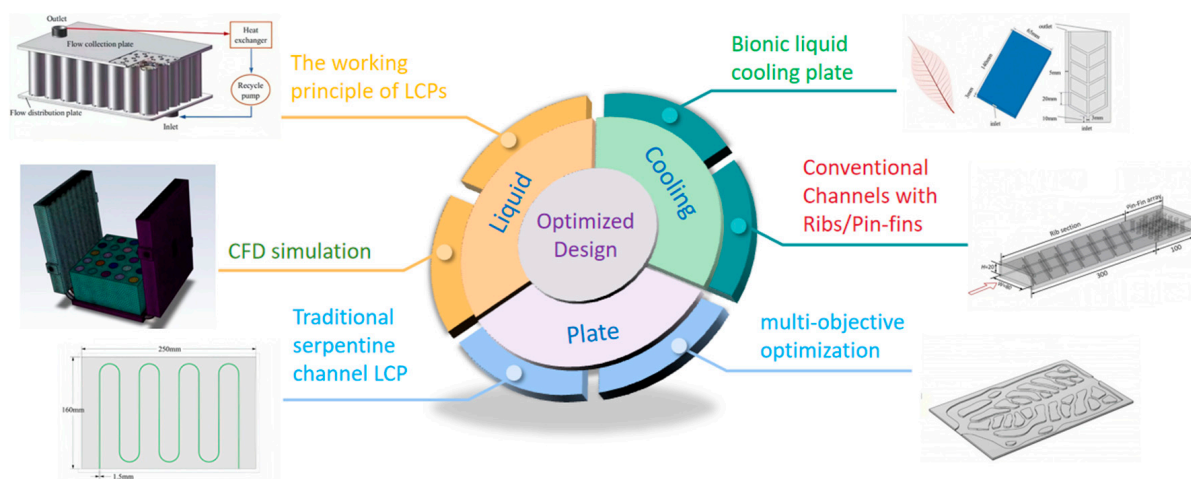


Figure 1: Table of contents.

Table 1: Comparison of different cooling technologies.

References	Cooling Method	Principle	Advantages	Limitations	Typical Applications
[5,10]	Air cooling	Forced/natural air convection over battery surface	Low cost, simple structure, easy maintenance	Low specific heat and thermal conductivity of air; limited cooling capacity under high-rate discharge	Low-power EVs, hybrid vehicles, stationary energy storage
[1,5,7]	Liquid cooling	Coolant (water/glycol) flowing through cold plates or direct immersion	High heat transfer coefficient, excellent temperature uniformity, proven reliability	Higher system complexity, sealing requirements, pumping power consumption	High-energy-density EVs (Tesla, BMW, Chevrolet)
[11–13]	PCM cooling	Latent heat absorption during solid–liquid phase change	Passive operation, good temperature uniformity, no parasitic power	Low thermal conductivity; full melting under sustained high loads; heavyweight	Short-duration high-load applications, hybrid systems
[14,15]	Heat pipe cooling	Two-phase evaporation–condensation cycle	Ultra-high equivalent thermal conductivity, isothermal operation	Limited contact area, complex integration, high cost	High-power local hotspots, aerospace applications

Within the liquid cooling system architecture, the liquid cooling plate (LCP) serves as the critical solid–fluid conjugate heat transfer interface. It is the component that directly contacts the battery module (via thermal interface materials) and through which the coolant flows to actively remove heat. Unlike the pump, radiator, or piping, which only transport or reject heat, the LCP’s internal channel geometry determines the local heat transfer coefficient, the spatial distribution of coolant flow, and the thermal resistance between the heat source and the coolant, as reviewed in the liquid-cooling BTMS design literature [1,9]. In other words, even with the same coolant, flow rate, and pump power, different LCP designs can yield substantial differences in battery maximum temperature uniformity and pressure drop performance [7,9]. Therefore, the LCP is widely recognized as the “performance bottleneck” of the liquid cooling system in both academic research and commercial applications [2,7], and its optimization directly dictates the upper limit of overall BTMS cooling capability.

The liquid cooling plate (LCP) is the core heat-exchange component of indirect liquid cooling systems. It plays a key role in transferring heat from the battery to the coolant efficiently. Its design parameters directly determine the BTMS cooling performance and energy consumption. These parameters include channel geometry (cross-sectional shape, width, depth), channel layout (series/parallel configuration, inlet/outlet locations and numbers), coolant selection, and material properties. As electric vehicle range and fast-charging requirements continue to rise, the heat generation rate of battery modules increases sharply. This places a growing thermal management burden on the LCP [16]. Under extreme fast charging (XFC) conditions, in particular, the battery heat generation rate can reach several times that of normal operation within a short period. This imposes stringent demands on the LCP’s transient response capability and heat dissipation limits.

At the same time, LCP design faces multi-objective conflicts. Improving heat dissipation often leads to higher pressure drop and increased pumping power. Pursuing better temperature uniformity may require more complex channel structures. Meanwhile, the limited space in vehicle applications imposes strict constraints on LCP volume and weight. Therefore, achieving an optimal trade-off among cooling performance, temperature uniformity, energy consumption, and structural compactness has become the core challenge in LCP optimization design [17].

Although extensive research has been conducted on liquid-cooled BTMS in both academia and industry, most existing reviews focus on performance research of a single cooling method or provide general summaries of various BTMS technologies. A systematic and in-depth review specifically targeting LCP optimization design is still lacking. Emerging technologies—such as structural improvement of LCPs, topology optimization of cooling channels, bionic channel design, nanofluid applications, and intelligent algorithm-driven multi-objective optimization—are continuously being developed. There is an urgent need to systematically review and comprehensively analyze these scattered research findings in order to reveal their underlying logic and development trends [18–20].

In response to this challenge, a substantial body of research has emerged, covering diverse aspects such as channel geometric optimization, bionic/fractal channel design, topology optimization, and surrogate-model-assisted multi-objective optimization. However, these contributions remain scattered across different application contexts, channel configurations, and optimization frameworks, making it difficult for researchers and engineers to obtain a holistic view of the current technical landscape. To fill this gap, the present review distinguishes itself from prior efforts in three key aspects: (i) it provides a cross-configuration comparative synthesis covering conventional, bionic, and topology-optimized channels within a unified analytical framework, rather than treating each in isolation; (ii) it systematically reviews surrogate-model-assisted multi-objective optimization strategies specifically for LCPs, with particular attention to model accuracy, sample-size limitations, and validation practices; and (iii) it critically evaluates practical engineering constraints—including manufacturability, experimental validation, and system-level integration—that are often overlooked in purely numerical optimization studies. This unique positioning is systematically contextualized against previous review efforts in Table 2, which summarizes the scope, coverage, and identified gaps of prior BTMS/LCP review articles alongside the specific contributions of the present work. By integrating these dimensions, this review aims to offer both a systematic reference for academic researchers and actionable guidance for engineering practitioners in LCP design.

Table 2: Comparison of previous review articles and the unique contributions of the present review.

References	Year	Review Scope	Coverage of LCP Optimization	Identified Gap/Limitation
Wu et al. [1]	2024	Liquid-cooling BTMS (general)	Moderate	Broad scope; lacks critical comparison of channel configurations
Khoharo et al. [2]	2025	BTMS global advancement (all methods)	Limited	Broad scope; lacks in-depth LCP optimization focus
Tete et al. [7]	2021	BTMS for EVs (all cooling methods)	Limited (brief summary)	Focus on system integration, not channel-level design
Zhao et al. [9]	2023	Liquid-cooling BTMS design improvement	Partial (parametric optimization only)	No coverage of bionic/fractal or topology-optimized channels
Fayaz et al. [17]	2021	BTMS thermal & structural optimization (general)	Partial (optimization methods)	Focus on algorithms, not channel configuration innovations
Rahmani et al. [20]	2024	BTMS performance enhancement (general)	Minimal	Emphasis on materials and general strategies, not structural optimization
This review	2026	LCP channel design & multi-objective optimization	Comprehensive	First systematic synthesis covering conventional, bionic/fractal, and topology-optimized channels within a unified optimization framework, with critical assessment of manufacturability and experimental-validation gaps

2 Literature Selection Methodology

To ensure transparency and reproducibility, a systematic literature search was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The Web of Science Core Collection and Google Scholar were searched using the following keyword combinations: (“liquid cooling plate” OR “cold plate”) AND (“battery thermal management” OR “BTMS”) AND (“channel design” OR “topology optimization” OR “bionic” OR “multi-objective optimization” OR “surrogate model”). Google Scholar was used as a complementary search engine to identify additional relevant studies not indexed in WoS. The search period was set from January 2015 to June 2026 to capture both foundational developments and recent advances. Only peer-reviewed journal articles written in English were considered.

Studies were included if they specifically addressed the design, structural optimization, or performance evaluation of liquid cooling plates for battery thermal management applications, and reported quantitative performance metrics such as maximum temperature, temperature difference, or pressure drop. Studies that focused solely on chip cooling, turbine-blade cooling, or general system-level thermal management without providing detailed cold-plate channel geometries were excluded unless their mechanistic insights were used for comparative analogy.

The initial search yielded 342 records from the two databases. After removing 92 duplicate records, 250 records were screened based on titles and abstracts. Subsequently, 125 full-text reports were sought for retrieval, of which 5 were not accessible. The remaining 120 reports were assessed in full text, leading to the exclusion of 10 records for reasons including irrelevance to LCP channel design, lack of quantitative performance data, and non-battery applications. Finally, 110 studies were included in this review. The detailed screening process is illustrated in Fig. 2.

It should be noted that, in addition to studies specifically focused on batteries, this review also cites a small number of studies from other heat transfer application areas—including chip cooling, turbine blade cooling, and fundamental research on microchannel flow—whose sole purpose is to elucidate general mechanistic principles (such as the generation of secondary flow, boundary layer separation, and the behavior of turbulence models). These studies are not presented as direct evidence of the performance of battery thermal management systems, and in this review, conclusions drawn from these studies are clearly distinguished from those derived from LCP studies specifically focused on batteries.

In accordance with the journal’s policy on the use of generative AI in manuscript preparation, the authors declare that AI-assisted tools were employed during the production of illustrative figures in this review. Specifically, PicDoc (an online AI-based drawing tool) was used to generate the initial conceptual drafts of Figs. 3–5. Subsequently, all figures were comprehensively redrawn and finalized by the authors using standard vector graphics tools to ensure professional quality and accuracy. The authors take full responsibility for the final content of all figures presented in this manuscript.

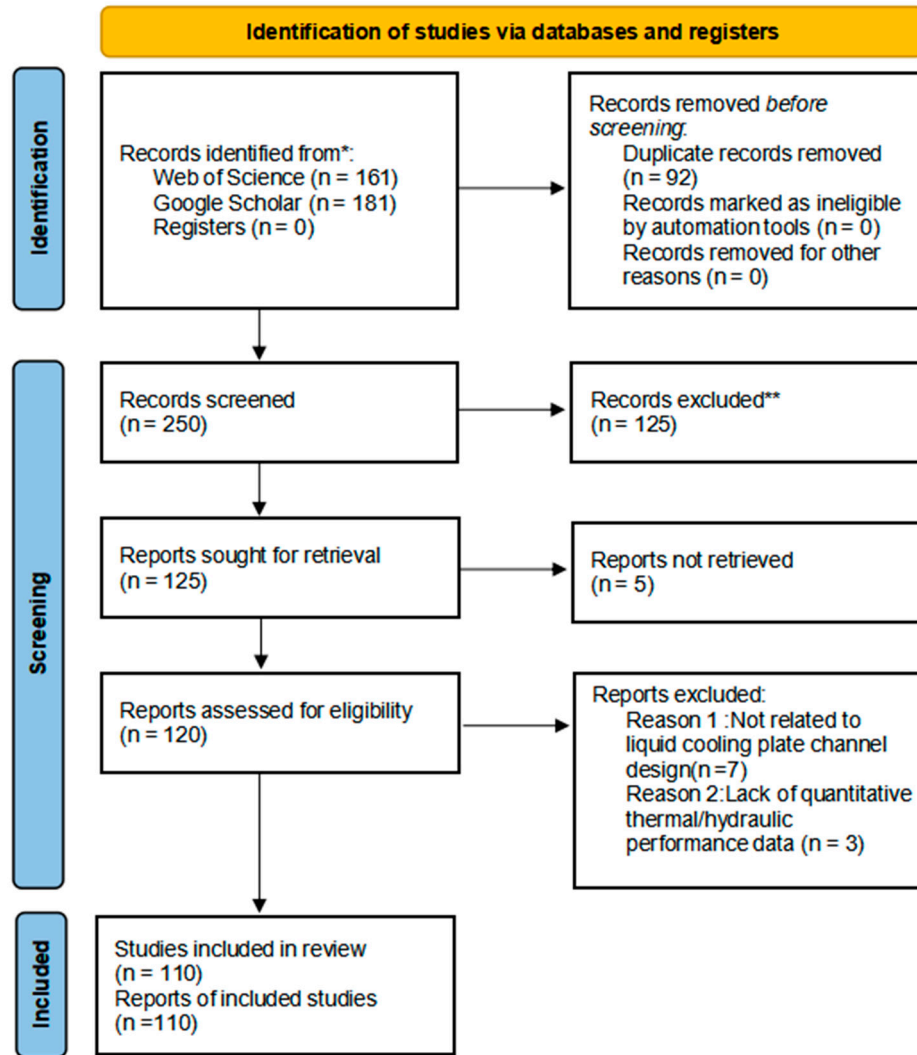


Figure 2: PRISMA flow diagram. Notes: *indicates that the number of records identified from each database and register (Web of science, google scholar, and registers) is reported separately, rather than as a combined total. ** Indicates the number of records excluded during the title and abstract screening stage. No automation tools were used for exclusion in this review (0 records marked as ineligible by tools); thus, all 125 excluded records were screened and excluded manually.

3 Research Objectives and Significance

This paper aims to provide a systematic literature review on the optimization design of liquid cooling plates (LCPs). The goal is to offer design references and theoretical support for the thermal management of high-power-density lithium-ion batteries in electric vehicles. Specifically, this study has four objectives. First, it systematically categorizes the basic structural types, working principles, and key design parameters of LCPs. This establishes a systematic cognitive framework for LCP optimization design. Second, it reviews improvement methods for conventional channel configurations and emerging design techniques—such as bionic flow channels and topology optimization—from multiple perspectives. These include cooling channel geometry, cold plate structure, coolant selection, and system integration. Third, it summarizes the applications of single-objective and multi-objective optimization methods in LCP design. These methods include genetic algorithms, particle swarm optimization, response surface methodology, and NSGA-II [21]. The review also analyzes their trade-off mechanisms when handling conflicting objectives such as cooling

performance, energy consumption, and pressure drop. Fourth, it identifies key challenges and knowledge gaps in current research and discusses future development directions for LCP optimization design.

This review distinguishes itself from previous BTMS/LCP reviews by being the first to systematically synthesize conventional, bionic/fractal, and topology-optimized channel designs within a unified optimization framework, while critically assessing manufacturability and experimental-validation gaps that prior reviews have largely overlooked.

The significance of this review is as follows. Most existing reviews are limited to performance summaries of single cooling methods. For instance, some reviews focus exclusively on air cooling [10] or PCM cooling [11], while others concentrate on liquid cooling performance [5] without addressing channel-level design optimization. They lack systematic synthesis and integration of LCP optimization design techniques. In particular, in recent years (particularly from 2020 to 2026), rapid advances in simulation technologies and optimization algorithms have generated numerous innovative achievements in the LCP design field. These include bionic flow channels, TPMS (Triply Periodic Minimal Surface, a porous structure with high specific surface area and superior heat transfer performance) structures, and topology-optimized cold plates (channel geometries automatically generated by mathematical optimization algorithms within a given design domain). A systematic review and critical evaluation of these latest developments is urgently needed. Furthermore, artificial intelligence is becoming increasingly integrated into BTMS in recent years. Machine learning models are now widely used for battery temperature prediction, thermal behavior modeling, and cooling strategy optimization. These tools provide new technical pathways for intelligent LCP design and real-time control. At the same time, the continuous impact of battery aging on heat generation rates demands that LCP design account for thermal management effectiveness over the entire lifecycle. This dimension has rarely been considered in existing optimization studies. By systematically integrating these scattered research findings, this paper aims to provide valuable references for both theoretical research and engineering practice in LCP optimization design. It also seeks to point out future directions for the development of battery thermal management technologies.

4 Principles of Liquid Cooling Plate Technology

4.1 Basic Structure and Classification

The liquid cooling plate (LCP) is the core heat exchange component of a liquid cooling system. Its basic function is to transfer heat from the heat source through the solid wall to the coolant flowing inside the channels. The flowing coolant then carries the heat away from the heat source region. Structurally, an LCP typically consists of a base plate, a cover plate, internal flow channels, and inlet/outlet fittings. Among these, the channel structure is the key factor determining heat transfer performance.

Based on the complexity and design philosophy of channel configurations, existing LCP structures can be roughly divided into three categories: conventional regular channel configurations, bionic/fractal channel configurations, and free-form channel configurations generated by topology optimization. Conventional regular channels include parallel straight channels, serpentine channels, and their improved variants (e.g., with turbulators/fins, variable cross-sections, or double-layer channels). These channels have regular geometric features and are easy to manufacture, making them the most widely used type in engineering applications. Bionic and fractal channels draw inspiration from the structural characteristics of efficient transport networks in nature, such as leaf vein/tree-like networks, spider web/honeycomb structures, and fish bone/vascular-like channels. Their goal is to achieve better flow and temperature uniformity with lower flow resistance. Topologically optimized channels are generated directly by mathematical optimization

algorithms within a given design domain, boundary conditions, and performance targets. They produce non-intuitive channel shapes and represent a frontier direction in LCP design.

From the perspective of spatial layout, LCPs can be classified as single-layer channel structures or multi-layer/three-dimensional channel structures. Most LCPs use a single-layer planar channel design, where the coolant flows and exchanges heat within a single plane. In recent years, some studies have proposed double-layer channel LCPs (ELCP) and three-dimensional cooling plates (3DCP). These designs arrange multiple channel layers in the vertical direction or place cooling surfaces around multiple sides of the battery. This increases the heat exchange area while improving temperature uniformity. For example, an enhanced double-layer LCP (ELCP) with dual-inlet/dual-outlet channels and an intermediate partition plate can reduce the battery temperature to 32.76°C under 3C discharge, showing significant improvement over single-layer designs [22]. Three-dimensional cooling plates arrange cooling channels at the bottom, sides, and even the top of the battery simultaneously. Under the same flow rate, they can substantially reduce the maximum temperature and decrease temperature differences between cells [23].

In addition, LCPs are primarily used in indirect cooling schemes. Under the indirect cooling architecture, the installation position of the LCP also shows a diversifying trend. Bottom placement is the most common form [24,25]. Some designs adopt side placement or double-side/triple-side surrounding layouts to accommodate different battery module structures and space constraints. For large-size prismatic batteries, side or three-side cooling schemes can effectively shorten the heat conduction path. This alleviates the temperature non-uniformity issue caused by the longitudinal conduction bottleneck in bottom-cooling schemes [26].

A schematic summary of the classification and structural variants of LCPs is presented in Fig. 3.

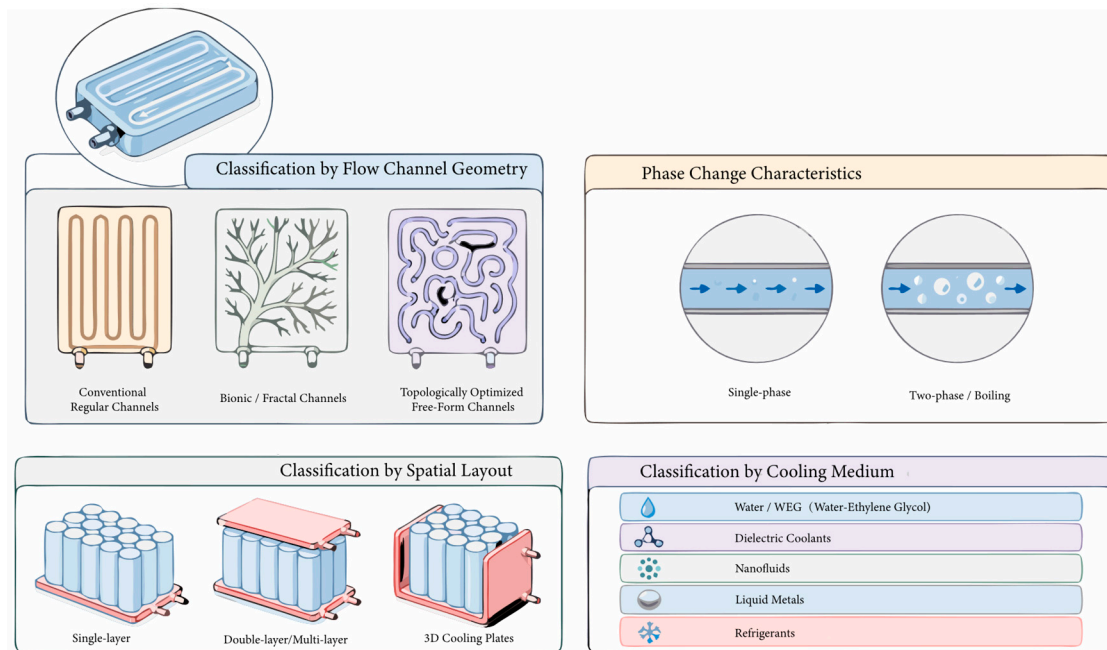


Figure 3: A schematic illustration of the classification of liquid cooling plates.

4.2 Working Principle

The working principle of an LCP is based on the coupled action of conduction and convection heat transfer. Heat generated from the surface of a heating element (e.g., a battery cell or power semiconductor chip) is first transferred to the LCP shell wall through contact conduction. Then, through convective heat

transfer between the wall and the coolant inside the channels, the heat is passed to the working fluid. Finally, the flowing coolant carries the heat away. This process involves heat conduction in the solid domain and convective heat transfer in the fluid domain. It is a typical fluid-solid conjugate heat transfer problem [27,28].

4.2.1 Heat Transfer Mechanisms

The physical mechanisms of enhanced heat transfer in liquid cooling plates can be understood from two perspectives: thermal boundary layer theory and flow structure. In smooth straight channels, the coolant gradually absorbs heat along the flow direction. The thermal boundary layer thickens continuously from the inlet section, causing the local convective heat transfer coefficient to decay along the path. To address this issue, existing studies have primarily introduced various channel structures to “reset” or “disrupt” the thermal boundary layer.

Secondary flow and vortex structures are among the core mechanisms for heat transfer enhancement in LCPs. By placing micro V-shaped ribs, oblique fins, pin fins, or other disturbance structures inside the channels, or by machining grooves/protrusions on channel walls, secondary flows perpendicular to the main flow direction can be induced [29]. Studies indicate that the twin counter-rotating “twist vortices” generated by V-shaped ribs can direct the mainstream cold fluid to directly scour the heat transfer wall, creating a three-dimensional flow effect. The resulting convective heat transfer enhancement is far superior to that of straight ribs, which only produce two-dimensional vortices by breaking the boundary layer [30,31]. Similarly, oblique fin structures generate lateral secondary flows driven by pressure differences between adjacent main channels. This enhances fluid mixing and maintains a high heat transfer coefficient with little increase in pressure drop [32]. In microchannel LCPs, the introduction of secondary microchannels can create high-intensity vortex zones near the downstream wall, improving the overall heat transfer performance by 57.1% compared to traditional straight channels [28].

Boundary layer re-initialization is another important enhancement mechanism. Oblique fins, interrupted fins, and similar structures are arranged in segments. This allows the flow boundary layer to redevelop at the inlet of each downstream structural unit. Because the thermal boundary layer is thinner and the temperature gradient steeper in the entry region, this mechanism keeps the local heat transfer coefficient at a high level. Research suggests that this “periodic reset” strategy is the fundamental reason why oblique-fin LCPs outperform traditional straight-channel designs in heat transfer performance.

Increasing the heat transfer area is also an effective way to raise total heat transfer. Adding extended surfaces such as fins and pin fins inside the channels, or machining micro-structures (grooves, dimples, etc.) on channel walls, can increase the effective heat transfer area without significantly enlarging the overall LCP dimensions [33,34]. However, increasing the area is often accompanied by higher flow resistance. Therefore, a balance must be sought between enhanced heat transfer and the penalty of pressure drop.

For two-phase LCPs—where the coolant undergoes boiling phase change inside the channels—the heat transfer mechanism is fundamentally different from that of single-phase flow. The latent heat of vaporization can absorb a large amount of heat, and the heat transfer coefficient is much higher than in single-phase convection. Nevertheless, the engineering application of two-phase LCPs still faces challenges such as flow pattern control, dry-out prevention, and sealing reliability [35,36].

4.2.2 Flow Characteristics

The flow characteristics inside a liquid cooling plate directly determine its convective heat transfer capability and system energy consumption. These characteristics are primarily influenced by channel geometry, inlet flow rate, and coolant physical properties.

Pressure drop and velocity distribution are two core indicators for characterizing flow behavior. Under a given channel geometry, increasing the coolant flow rate raises the velocity and turbulence intensity, thereby enhancing convective heat transfer. However, it also leads to higher pressure drop and pumping power. Studies generally find that the improvement in cooling performance from increasing flow rate has a saturation effect. Beyond a certain threshold, further flow rate increases yield only limited temperature reduction, while pressure drop continues to rise [37]. Therefore, LCP optimization design must determine a reasonable flow rate operating range.

Channel layout has a significant impact on flow uniformity. In parallel channels, the coolant tends to flow along paths of lower resistance due to differences in branch resistance. This results in some channels receiving insufficient flow, leading to localized deterioration of heat transfer. Optimizing the inlet/outlet positions and arrangements can substantially improve flow uniformity. Studies show that a dual-inlet dual-outlet layout achieves the best temperature control effect with the lowest pressure drop [27]. In addition, the symmetric double-spiral channel design reduces corner stagnation zones through its semi-circular rounded corners, giving better flow field uniformity than traditional serpentine and parallel channels [38].

The spatial arrangement of channels also affects flow characteristics. The double-layer channel LCP (ELCP) significantly reduces system pressure drop by shortening the length of each individual channel. Compared to a single-layer design, the double-layer dual-inlet dual-outlet structure can reduce pressure drop by 79.8% [22]. Three-dimensional cooling plates (3DCP) enlarge the total channel cross-sectional area through multi-side cooling. This allows a substantial reduction in both required flow rate and pressure drop while meeting the same temperature control targets [23].

The coolant temperature rise along the flow path is another important factor in flow characteristics. As the coolant flows through the LCP, it continuously absorbs heat, and its own temperature gradually increases along the flow direction. This reduces the heat transfer temperature difference in downstream regions, creating a temperature gradient along the coolant flow direction in the battery module or electronic device. Modular LCP design divides a large cold plate into multiple independent sub-domains. This can effectively mitigate the coolant temperature rise effect by more than 50% [39]. The symmetric double-spiral channel design suppresses the accumulation of temperature gradients along the path through an alternating layout of hot and cold fluid channels.

The coupled conduction–convection heat transfer process in a typical LCP is schematically illustrated in Fig. 4. And Fig. 5 provides a consolidated summary of the key heat-transfer and flow characteristics of LCPs discussed above.

4.3 Key Design Parameters

The performance of an LCP depends on the coupled effects of multiple design parameters. These parameters can be grouped into three major categories: channel geometry, channel layout, and selection of materials and coolant.

4.3.1 Channel Geometry

Channel geometry is the most critical factor affecting the heat transfer and flow performance of an LCP. The main parameters include channel cross-sectional shape, characteristic dimensions (width, height/depth), and channel length.

Cross-sectional shape: Common channel cross-sections include rectangular, trapezoidal, triangular, circular, and semi-circular shapes. In microchannel LCPs, the rectangular cross-section is the most widely used form [28,34]. Studies on enhanced structures such as V-shaped ribs show that ribs with different

cross-sectional shapes produce significantly different heat transfer performance. Among them, V-shaped ribs with a triangular cross-section achieve the best heat transfer performance [30]. For groove structures, the rectangular groove exhibits the highest overall performance evaluation criterion (PEC) among four shapes (elliptical, rectangular, trapezoidal, and triangular) [28]. For two-phase flow applications, channels with a low aspect ratio ($AR \leq 1$) are more favorable for maintaining flow boiling stability [35].

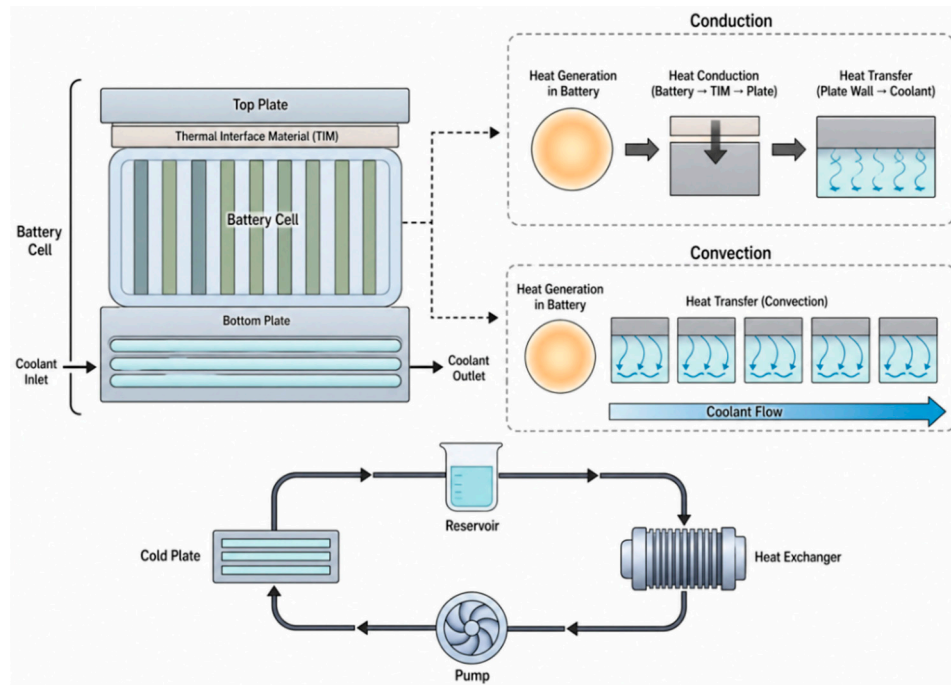


Figure 4: Generic schematic diagram illustrating the working principle of LCPs.

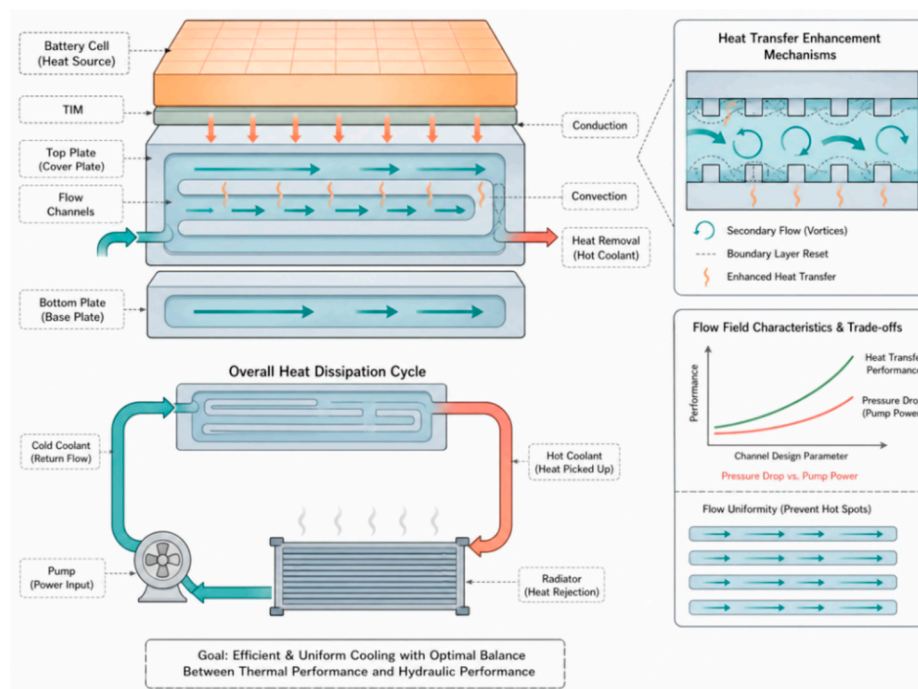


Figure 5: Summary of the working principle of LCPs.

Characteristic dimensions: Channel width and height (or depth) directly affect the hydraulic diameter of the flow passage, which in turn influences the convective heat transfer coefficient and flow resistance. In general, reducing the hydraulic diameter increases the heat transfer area-to-volume ratio and improves the convective heat transfer coefficient. However, it also significantly increases the pressure drop [35]. For single-phase LCPs, the optimal aspect ratio typically ranges from 5 to 16.6. A higher aspect ratio is beneficial for increasing the heat transfer area within a limited footprint. Increasing channel width can reduce the maximum temperature and pressure drop to some extent, but may lead to a slight increase in temperature difference [27].

Rib/fin and turbulator parameters: When placing ribs, pin fins, fins, or other enhanced structures inside the channels, their height, spacing, and arrangement have a significant impact on performance. Optimization studies on pin-fin height indicate that there exists an optimal height that maximizes the overall thermo-hydraulic performance. If the rib height is too low, the enhancement effect is insufficient; if it is too high, the flow resistance increases substantially [34]. Fin spacing also has an optimal value; deviating from this value can reduce heat transfer performance by approximately 3 K. For micro V-shaped ribs added to channels, the cross-sectional shape and angle of the ribs also affect secondary flow intensity and the pressure drop penalty [30].

4.3.2 Channel Layout

Channel layout involves the spatial organization of channels, including series/parallel configurations, inlet/outlet positions and numbers, number of channel layers, and the overall channel pattern.

Series/parallel configuration: Series channels have a simple structure and relatively high flow velocity, but suffer from a significant temperature rise along the flow path. Parallel channels can reduce the total pressure drop, but carry the risk of uneven flow distribution. In practice, combined series-parallel structures are often used to leverage the advantages of both. Studies find that increasing the number of channels is not always better. More channels reduce the flow velocity in each individual channel and aggravate the temperature rise along the path. In fact, a single-channel LCP can outperform multi-channel designs in heat dissipation performance [40]. The appropriate number of channels should be determined based on the flow rate and cooling requirements.

Inlet/outlet positions and numbers: The positions and numbers of inlets and outlets significantly influence flow uniformity and temperature field distribution. For parallel channels, proper inlet/outlet arrangement can effectively improve the uniformity of flow distribution among branches. Studies show that a dual-inlet dual-outlet layout not only achieves the lowest pressure drop, but also provides the best battery temperature control, offering a clear advantage over single-inlet single-outlet configurations [27]. For energy storage battery systems, the symmetric double-spiral channel design places the inlet and outlet adjacent to each other with semi-circular rounded transitions. This gives better flow field uniformity than traditional serpentine channels and commercial parallel channels [41,42].

Channel patterns: Different channel patterns—such as serpentine, parallel straight, spiral, wavy, and fractal designs—determine the overall flow path and heat transfer characteristics of the coolant inside the LCP. The serpentine channel is one of the most commonly used configurations. Its advantages include a simple structure and a relatively long effective flow length. However, it suffers from a large temperature rise along the path and localized hot spots [24,26]. Parallel straight channels have a short flow path and low pressure drop, but are prone to uneven flow distribution between channels. Fractal/bionic channels, which mimic the multi-level branching structures of natural transport networks, show advantages in flow uniformity and temperature consistency. The symmetric double-spiral channel arranges hot and

cold fluids alternately adjacent to each other through its spiral layout, suppressing the accumulation of temperature gradients along the path. Its overall performance (PEC) is 21.2% higher than that of the serpentine channel [38]. Fig. 6 visually illustrates the geometric layouts of four representative channel configurations, and Table 3 compares their respective advantages.

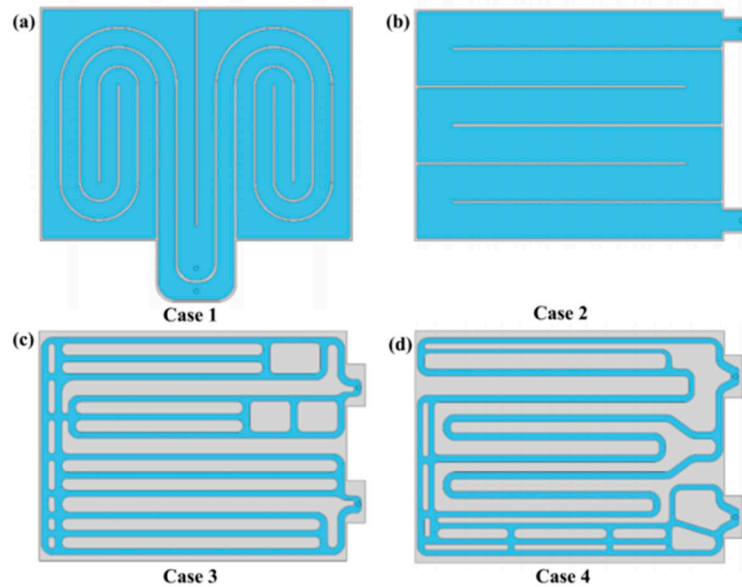


Figure 6: Liquid cooling plates with different channel structures [38]: (a) case 1: symmetrical double-helix channel; (b) case 2: serpentine channel; (c) case 3: parallel channels optimized for flow uniformity; (d) case 4: parallel channels optimized for temperature uniformity.

Table 3: Advantages for four different LCPs [38].

	Type	Advantages
Case 1	Symmetrical Double-Spiral Channel	Uniform flow field and enhanced thermal performance
Case 2	Serpentine Channel	Simple structure and high heat exchange efficiency
Case 3	Parallel Channel	Mature technology with practical applications in battery packs
Case 4	Parallel Channel	Redesigned for improved temperature uniformity

Channel layers and three-dimensional arrangement: Single-layer channel structures are simple and easy to manufacture. However, for large-format or high-power-density heat sources, a single-layer structure may not meet the heat transfer requirements. Double-layer channels and three-dimensional cooling plates provide a larger heat transfer area and shorter heat conduction paths by adding channel layers in the vertical direction or placing cooling surfaces around multiple sides of the battery. However, they also come with higher structural complexity and manufacturing costs [43–46].

To facilitate cross-study comparison and improve readability, Table 4 summarizes representative LCP studies across different channel configurations, listing key geometric parameters, operating conditions, and reported performance metrics.

Table 4: Comparison of representative LCP studies: channel configurations, design parameters, and key performance metrics.

Reference	Channel Type	Key Geometric Parameters	Coolant	Heat Source Condition	$T_{\max}/\Delta T_{\max}$	ΔP or Pumping Power
Lv et al. [27]	Central bifurcated mini-channel (dual-inlet dual-outlet)	Main channel width 2–7 mm; branch angle variable	Water	Prismatic cell, 2C discharge	33.64°C/6.89°C	152 Pa (at 0.8 g/s)
Zhang et al. [46]	Double-layer enhanced LCP (ELCP)	Channel height 3 mm; 11 cooling channels	Water	Prismatic cell, 3C discharge	32.76°C/3.76°C	79.8% reduction vs. SLCP
Xia et al. [47]	Bionic leaf-vein/tree-root channel	Main channel angle 45°; branch angle 120°; channel height 4 mm	Water	Prismatic cell	35.51°C	14.2% reduction vs. conventional
Wang et al. [48]	Bionic spider-web channel	Channel width 3 mm; channel number 11; angle 120°	Water	Pouch cell, 3C discharge	37.89°C/8.86°C	27.06 Pa
Zhan et al. [49]	Topology-optimized channel (with bionic initial solution)	Density-field threshold; spline smoothing	Water	Prismatic cell	0.71°C reduction vs. OCP	16.02 Pa (71.25% reduction vs. OCP)
Lai et al. [22]	Straight channel with grooves & secondary microchannels	Groove shape: rectangular; secondary channel width 0.5 mm	Water–glycol (1:1)	Prismatic cell, 2C discharge	0.59 K reduction vs. smooth channel	—
Pu et al. [35]	Stereoscopic 3DCP (three/four-side cooling)	Battery size 65 × 18 × 140 mm; cooling on bottom + sides + middle	Water–glycol (1:1)	Prismatic cell, 2.5C discharge	306.5 K/5.1 K	6.0% of BCP pumping power
Jin et al. [32]	Ultra-thin LCP with oblique fins	Main channel width 2.2 mm; oblique slot width 2 mm; fin length 5.6 mm	Water	Prismatic cell (180 × 115 mm), 1240 W	4.1°C lower than straight channel at high load	—

As summarized in Table 4, the comparison reveals that bionic and topology-optimized channels generally exhibit superior temperature uniformity and lower flow resistance compared to conventional straight or serpentine designs, while double-layer and three-dimensional configurations offer enhanced cooling capacity at the cost of structural complexity. However, direct quantitative comparisons remain challenging due to differences in heat loads, cell dimensions, coolant types, and flow rates across studies.

4.3.3 Material and Coolant Selection

The selection of housing materials for LCPs involves balancing thermal conductivity, structural strength, corrosion resistance, and weight. Aluminum and its alloys are the most widely used materials due to their low density, good thermal conductivity, and moderate cost, while copper offers superior thermal conductivity for high-heat-flux applications at the expense of greater weight and cost. Manufacturing methods—including brazing, friction stir welding, and chemical etching—must be chosen with consideration of cost, sealing reliability, and achievable channel precision. Corrosion protection, typically achieved through surface treatments or corrosion inhibitors, is essential for long-term durability.

Coolant selection is governed by thermophysical properties that directly affect heat transfer coefficient and flow resistance. Water remains the most common coolant due to its high specific heat and thermal conductivity, with water-ethylene glycol mixtures used where freeze protection is required. Advanced coolants such as nanofluids and dielectric fluids offer enhanced thermal performance but face practical barriers including particle sedimentation, high pumping power, cost, and sealing requirements [50,51]. In engineering practice, inhibited propylene glycol/water coolants offer a mature and reliable balance of freeze

protection and corrosion inhibition. The choice of coolant must also consider compatibility with system materials and the specific operating temperature range.

4.4 Performance Evaluation Metrics and Engineering Application

The performance evaluation of LCPs requires a comprehensive assessment across three dimensions: thermal performance, flow performance, and overall performance. Thermal performance is primarily characterized by the maximum temperature ($T_{\max}$), which directly relates to battery safety and lifespan, and the maximum temperature difference ($\Delta T_{\max}$), which reflects temperature uniformity across the cold plate. Flow performance is quantified by pressure drop (ΔP) and pumping power, where lower values indicate reduced auxiliary energy consumption. Since these objectives inherently conflict—heat transfer enhancement typically increases flow resistance—researchers have proposed various overall performance criteria such as PEC (Performance Evaluation Criterion) and EI (Efficiency Index) to balance thermal and hydraulic trade-offs. Multi-objective optimization methods are commonly employed to identify optimal compromises among $T_{\max}$, $\Delta T_{\max}$, and ΔP , with their relative priorities varying across applications: EV battery thermal management emphasizes lightweight design and low energy consumption, energy storage systems prioritize long-term economic viability and temperature uniformity, and server chip cooling demands high heat flux capacity with strict pressure-drop limits.

Beyond these performance metrics, practical engineering constraints—including manufacturability, cost, sealing reliability, pressure limits, coolant compatibility, long-term durability against blockage and corrosion, and pumping energy consumption—are equally decisive in determining the viability of an LCP design. Conventional straight or serpentine channels benefit from mature manufacturing processes (e.g., milling, brazing, friction stir welding) and low fabrication costs, with established sealing solutions and well-understood pressure limits as demonstrated in experimental studies on mini-channel cold plates [52], making them the preferred choice for mass-produced EV battery packs; however, their performance ceiling is limited, and design improvements typically increase flow resistance. Bionic channels offer superior temperature uniformity and lower pressure drop, but their complex three-dimensional topologies pose significant challenges for conventional machining, requiring additive manufacturing or specialized casting that increases cost, introduces minimum feature-size constraints, and complicates sealing. Topology-optimized channels represent the performance frontier, yet their irregular geometries demand advanced fabrication techniques (e.g., selective laser melting) and extensive post-processing; as Cova et al. [53] demonstrated through CFD modeling of additively manufactured cold plates, minimum feature-size constraints and surface roughness effects can compromise the theoretical performance gains predicted by optimization algorithms. They also face unresolved challenges in sealing reliability under pressure cycling, long-term corrosion resistance in aggressive coolant environments, and susceptibility to blockage in micro-scale features as discussed in recent studies on advanced coolants and topology-optimized designs. Coolant compatibility and long-term degradation—including particle sedimentation in nanofluids and corrosion of channel walls—remain underinvestigated in the literature. Pumping energy, however, is directly addressed through pressure-drop metrics, which serve as a reliable proxy for parasitic losses. From a design-priority perspective, conventional channels are most practical for cost-sensitive, high-volume production; bionic designs are suited for moderate-volume applications where improved temperature uniformity justifies higher manufacturing costs; and topology-optimized channels are appropriate for ultra-high-performance scenarios (e.g., extreme fast charging or aerospace) where thermal constraints outweigh cost and reliability concerns. These engineering trade-offs should be explicitly weighed alongside thermal performance in any practical LCP selection or optimization process.

5 Fundamentals of Simulation Methods for Liquid Cooling Plates

In the design and optimization of liquid cooling plates, Computational Fluid Dynamics (CFD) simulation has become an indispensable core tool. Through numerical simulation, researchers can rapidly evaluate the thermo-hydraulic performance of different channel configurations, geometric parameters, and operating conditions without the need for extensive physical prototype fabrication. This significantly shortens the development cycle and reduces experimental costs. This chapter systematically presents the fundamental theories, key methodologies, and practical implementation points involved in LCP simulation. The coverage includes the role of simulation, governing equations and numerical methods, turbulence model selection, mesh generation, boundary conditions and solver settings, as well as a comparison of mainstream simulation software.

5.1 The Role of Simulation in LCP Optimization

At the engineering application level, simulations have been widely used to diagnose localized overheating and uneven flow distribution [54], to evaluate LCP designs for additive manufacturing using experimentally calibrated models, and to support scheme selection through transient simulations capturing SOC-related thermal behavior [55] and the combination of parameter screening based on orthogonal design with multi-objective optimization [56]. However, the credibility of these simulation results fundamentally depends on rigorous experimental validation; studies that integrate CFD modeling with experimental test benches establish a closed-loop “experiment-simulation-optimization” paradigm, ensuring the reliability of subsequent parameter studies and optimization conclusions [57,58]. In summary, CFD simulations play four key roles in LCP optimization: revealing flow and heat transfer mechanisms through full-field physical information; rapidly evaluating design schemes; enabling multi-objective optimization; and, following thorough validation, partially replacing experimental work to reduce R&D costs.

5.2 Governing Equations and Numerical Methods

The flow and heat transfer in LCPs are governed by the steady or transient incompressible Navier-Stokes and energy equations, which are discretized using the finite volume method with a conjugate heat transfer approach to couple the solid and fluid domains.

5.3 Turbulence Model Selection

For laminar flows, the Navier-Stokes equations are solved directly, while for turbulent flows—which span a wide Reynolds number range in LCP applications—the Realizable $k-\varepsilon$ model is most commonly used for its robust convergence and engineering accuracy, although scale-resolving methods may be required for microchannel flows with significant inlet or separation effects [59–63].

5.4 Mesh Generation

Mesh generation is one of the most critical and time-consuming steps in CFD pre-processing, as its quality directly affects the accuracy and convergence of the numerical solution. The solution domain must be discretized into control volumes or elements with appropriate refinement. The choice of mesh type depends on geometric complexity: structured meshes suit regular geometries, while unstructured or polyhedral meshes provide better adaptability for complex internal channel structures in LCPs. A representative meshing example for a BTMS cold-plate model, including a polyhedral volume mesh, localized refinement near channel walls, and grid-independence verification, is illustrated in Fig. 7. To provide a systematic overview of

mesh-generation practices and facilitate cross-study comparison, Table 5 summarizes the mesh type, element count, y^+ value, and grid independence criteria adopted in representative LCP simulation studies.

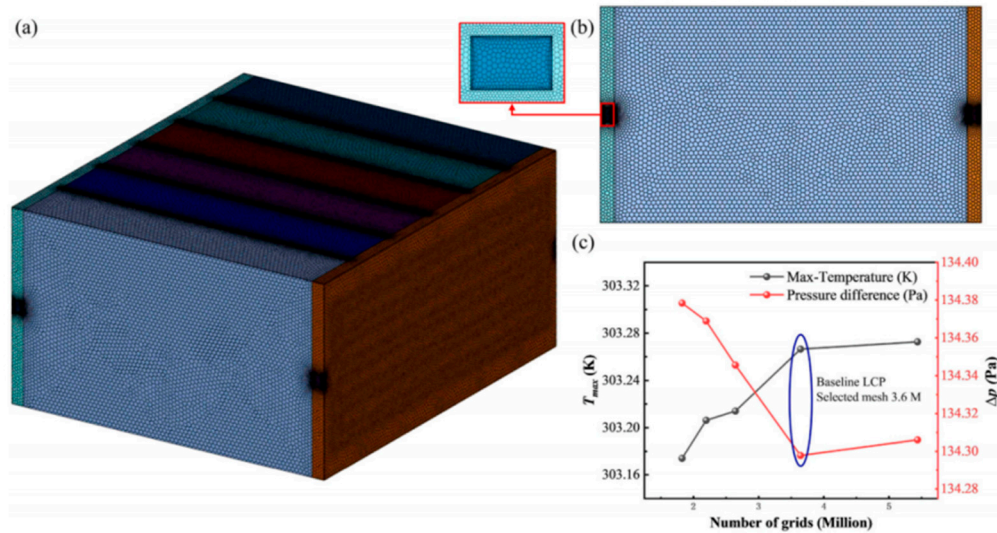


Figure 7: Meshing model of BTMS [22]: (a) polyhedral meshing view. (b) Front view and local view; (c) grid independence test.

Table 5: Summary of mesh generation practices in representative LCP CFD studies.

Reference	Software	Mesh Type	Element Number	y^+ Value	Grid Independence Criterion
Jayarajan & Azimov [64]	STAR-CCM+	Unstructured	Not explicitly stated	(laminar)	Results validated with literature
Cova et al. [53]	COMSOL Multiphysics	Finite element mesh	Not explicitly stated	(laminar)	Calibrated with experiments
Narvaez et al. [54]	STAR-CCM+	Unstructured (polyhedral)	20–34 million	Not reported	Convergence test performed
Akbarzadeh et al. [58]	ANSYS Fluent	Unstructured	Not explicitly stated	Not reported	Convergence test performed
Pulugundla et al. [55]	STAR-CCM+	Polyhedral + prism layers	~11 million	<1	GCI < 3%
Panchal et al. [65]	STAR-CCM+	Polyhedral + prism layers	Not explicitly stated	~5	Mesh sensitivity study
Wei et al. [66]	FLUENT 5.5	Structured hexahedral + TGrid (dimple region)	565,166/816,627	(laminar)	Deviation < 0.2% when mesh doubled

5.5 Boundary Conditions and Solver Settings

Correct specification of boundary conditions is fundamental to obtaining reliable CFD solutions. In LCP simulations, the inlet is typically defined as a mass-flow or velocity inlet with specified coolant temperature, the outlet as a pressure outlet, and no-slip conditions are applied to solid walls. Thermal boundary conditions vary by objective: constant heat flux for channel comparison, or conjugate heat transfer with volumetric heat sources for battery-level studies. Solver settings employ the SIMPLE algorithm for pressure-velocity coupling, with second-order upwind schemes for convective terms and residuals reduced to 10^{-6} (energy) and 10^{-4} (flow), supplemented by monitoring key physical quantities for convergence.

5.6 Comparison of Mainstream Simulation Software

The three major commercial LCP simulation tools—ANSYS Fluent, STAR-CCM+, and COMSOL Multiphysics—differ in numerical methods and optimal uses. Fluent is the dominant choice for battery

module-level LCP, with robust physical models and conjugate heat transfer. STAR-CCM+ excels in complex serpentine, bionic, and topology-optimized channels. COMSOL is ideal for tightly coupled fluid-heat-solid-electrochemistry problems but is less efficient for large-scale fluid flows. Table 6 summarizes their numerical methods, advantages, limitations, and recommended scenarios.

Table 6: Comparison of mainstream simulation software for LCP simulations.

Software	Core Method	Key Strengths	Main Limitations	Recommended Applications
ANSYS Fluent	Finite Volume Method (FVM)	Mature turbulence/multiphase/PCM models; robust conjugate heat transfer; extensively validated in BTMS.	Steep learning curve; meshing requires separate tools; high cost for transient simulations.	Battery module LCPs; PCM-coupled hybrid cooling; transient charge/discharge simulations.
STAR-CCM+	FVM and polyhedral mesh	Polyhedral meshing reduces cell count; efficient parallel computing; integrated workflow; complex geometry handling.	Higher cost; less multiphysics coupling than COMSOL; fewer academic BTMS users.	Serpentine/bionic/topology-optimized channels; large-scale module simulations (>10M elements).
COMSOL Multiphysics	Finite Volume Method (FVM)	Unified multiphysics (fluid + thermal + structural + electrochemical); equation customization.	Lower efficiency for large fluid problems; slower turbulent convergence.	Coupled electrochemistry–thermal–structural problems; topology optimization; additively manufactured LCPs.

5.7 CFD Validation and Uncertainty Analysis

A critical examination of the reviewed LCP simulation literature reveals several recurring weaknesses in validation practice. Mesh independence verification is frequently reported, yet the criteria for declaring independence are inconsistent across studies—some adopt quantitative thresholds while others rely on qualitative judgment—making cross-study comparisons of numerical accuracy difficult. Experimental validation, when performed, is typically limited to a single operating condition, which confirms model performance at one point but does not guarantee predictive reliability across the full range of relevant conditions. Moreover, many studies validate only thermal predictions while neglecting hydraulic performance, or *vice versa*. Critically, contact thermal resistance between the battery and cold plate—which can introduce temperature deviations of several degrees—is rarely measured or incorporated into simulation models, and the non-uniform nature of heat generation within actual battery cells is often oversimplified.

Quantitative uncertainty analysis is conspicuously absent from the vast majority of studies. The combined effects of mesh discretization error, turbulence model selection, and experimental measurement error on final predictions are seldom quantified, leaving the confidence intervals of reported performance metrics unknown. This observation is consistent with the findings of recent LCP simulation studies, where numerical predictions are frequently reported without accompanying uncertainty bounds. This lack of uncertainty quantification hinders meaningful comparison between studies and limits the engineering value of optimization conclusions. To enhance the credibility and practical utility of LCP simulation research, future studies should adopt more rigorous protocols: validate models against multiple independent datasets covering diverse operating conditions, explicitly report mesh independence criteria, quantify contact thermal resistance where applicable as demonstrated in experimental-numerical validation studies [52,58], and implement systematic uncertainty quantification to establish confidence bounds on key predictions following established practices in CFD validation [53,65,67].

6 Conventional Channel Configurations

6.1 Parallel Straight Channels

Parallel straight channels represent the most basic and widely used channel configuration for liquid cooling plates. They feature a simple structure and are easy to manufacture, making them suitable for large-area heat dissipation scenarios. However, their primary limitation is an inherent flow maldistribution problem: channels near the inlet and outlet receive disproportionately high flow rates, while those in the middle receive insufficient flow, leading to non-uniform temperature distribution across the cold plate [68].

To address this limitation, researchers have pursued two main strategies. The first involves modifying manifold structures and channel geometric parameters to redistribute flow more evenly across all channels [69,70]. The second introduces flow obstructions—such as ribs, cavities, or wavy paths—into the channels to disrupt thermal boundary layer growth and enhance fluid mixing. A recurring design principle across many studies is that introducing additional flow resistance in the central channels can effectively divert coolant toward the peripheral channels, thereby improving both temperature uniformity and overall heat transfer. The effectiveness and trade-offs of these approaches are well illustrated by Imran et al. [68], who systematically compared four modified configurations of a streamline-shaped cold plate against the original design. Fig. 8 shows the geometric layouts of these five structures, while Table 7 compares their quantitative performance metrics and comprehensive evaluation metrics.

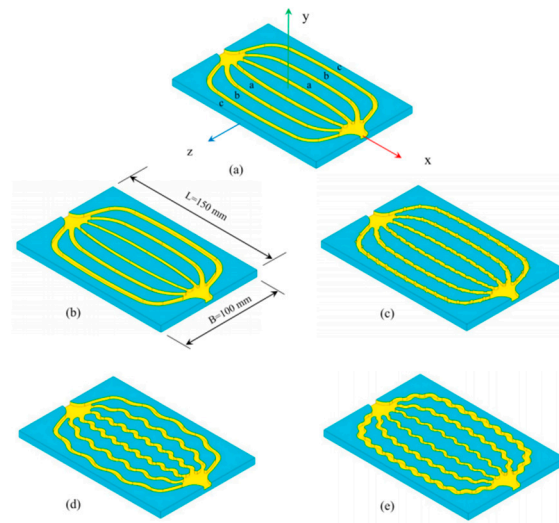


Figure 8: Cooled plate with different channel configurations [68]. (a) Original streamline shape cold plate; (b) variable channel width streamline shape cold plate; (c) obstructed channel streamline shape cold plate; (d) variable wavelength wavy channel streamline shape cold plate; (e) variable width wavy channel streamline shape cold plate.

As shown in Table 7, all four modified configurations achieve more uniform flow distribution than the original design. The results also reveal a clear and recurring pattern: the most aggressive modifications—combining variable widths with wavy paths—deliver the greatest thermal enhancement and best temperature uniformity, but at the cost of substantially higher pressure drop. In contrast, the simplest modification—varying channel widths alone—offers the most balanced overall performance, achieving the highest comprehensive evaluation criterion despite moderate thermal improvement. This pattern suggests that design complexity does not linearly translate to superior overall performance; simpler modifications may be more effective when both thermal and hydraulic performances are jointly considered.

Table 7: Comparison of performance among LCP with different channel configurations [68].

Configuration	Description	Misdistribution Factor	Nu Improvement	ΔP Increase	Temperature Non-Uniformity Index Reduction	Comprehensive Evaluation Criterion
Conf. (a)	Original SSCP (equal channel width)	0.2026	Baseline	Baseline	Baseline	Baseline
Conf. (b)	Variable-width channels	0.0908	+6.3%	+4%	−7.5%	3.07
Conf. (c)	Obstructed channels (ribs + cavities)	0.0633	+9.1%	+24%	−11.9%	2.48
Conf. (d)	Variable-wavelength wavy channels	0.0242	+7.7%	+31%	−9.7%	2.60
Conf. (e)	Variable-width wavy channels	0.1512	+12%	+54%	−14.8%	2.18

Despite these advances, several challenges remain unresolved. First, the vast majority of parallel-channel optimization studies rely on steady-state numerical simulations under idealized conditions, with limited experimental validation. Second, most studies optimize for a single discharge rate or heat load, leaving the robustness of optimized designs under variable operating conditions largely unverified. Third, the manufacturing complexity and cost associated with modified channel geometries—particularly those involving non-uniform widths or wavy paths—are rarely addressed, creating a gap between academic research and industrial application. Fourth, the conclusions drawn from a specific cold plate geometry and channel count are often assumed to be generalizable, yet there is little systematic evidence that optimized designs for one scale or configuration translate effectively to others. These limitations suggest that future research should prioritize experimental validation under realistic driving cycles, develop adaptive designs that perform well across a range of operating conditions, and explicitly account for manufacturability constraints in the optimization process.

6.2 Serpentine Channels

Serpentine channels represent another classic LCP configuration that primarily enhances heat transfer by lengthening the coolant flow path, thereby increasing the effective heat transfer area and residence time. Researchers have extensively optimized the number of channels, their orientation, and the inlet/outlet configurations. Increasing the number of channels can improve temperature uniformity, but when the optimal number is exceeded, the benefits gradually diminish because additional channels reduce flow velocity and exacerbate temperature rise along the path. The orientation relative to the battery surface also significantly affects cooling performance; longitudinal arrangements generally outperform transverse ones due to better heat transfer coverage. Regarding inlet/outlet arrangements, dual-inlet, dual-outlet configurations consistently outperform single-inlet, single-outlet designs in terms of thermal management and hydraulic performance, with counter-current arrangements providing superior temperature uniformity. Modular manifold designs have also been explored to enhance flexibility for varying cooling requirements. Despite these advances, the inherently longer flow path in serpentine channels inevitably increases pressure drop; therefore, the benefits of increasing the number of channels or adopting a dual-inlet configuration must be balanced against the associated losses in pumping power. A recurring theme in serpentine channel research is that structural complexity leads to improved thermal performance but comes at the expense of hydraulic performance; thus, careful multi-objective optimization is required to determine the optimal balance for a specific application [71–76].

6.3 Other Improved Channel Designs and Enhanced Structures

Beyond parallel and serpentine configurations, researchers have explored various enhancement strategies to push the performance limits of conventional channels. These can be broadly categorized into three approaches. The first involves introducing turbulators, ribs, pin-fins, or dimples inside channels to disrupt thermal boundary layer development and induce secondary flows. While these structures effectively enhance convective heat transfer by promoting fluid mixing and boundary-layer re-initialization, they generally introduce additional flow resistance—though in some configurations, the secondary flows can suppress downstream flow separation, partially offsetting the pressure-drop penalty. The second approach employs variable cross-sections or wavy channel profiles, which improve flow distribution uniformity and enhance heat transfer through periodic flow redirection and vortex generation [77,78]; however, the pressure-drop penalty varies considerably with geometric complexity, and simpler modifications often achieve better overall thermo-hydraulic balance. The third approach utilizes double-layer or multi-layer channel arrangements to increase heat transfer area within a constrained footprint, offering significant improvements in heat transfer coefficient with only modest pressure-drop increases, though at the cost of greater manufacturing complexity and additional sealing requirements. A common theme across all enhancement strategies is the inherent trade-off between thermal improvement and hydraulic penalty: more aggressive modifications yield greater heat transfer gains but at higher pumping power costs. The choice of enhancement technique should therefore be guided by application-specific priorities—whether the design emphasizes maximum cooling capacity, minimal energy consumption, or manufacturability. Systematic multi-objective optimization is often necessary to identify the optimal balance for a given application.

6.4 Limitations of Current Approaches

Although research on conventional channel configurations has yielded substantial results, several limitations remain.

First, geometric parameter optimization of channels is mostly conducted in a “trial-and-error” manner or through local parameter sweeping. A global topological innovation of the flow channel is lacking. Even when orthogonal experiments or response surface methods are employed, the optimization space remains confined by the initial configuration, making it difficult to break free from the constraints of existing design paradigms. This limitation is particularly pronounced for serpentine and double-layer channels, where the number of geometric variables (e.g., channel count, layout direction, and layer arrangement) is large, and their interactions are complex; most studies vary only one parameter at a time, making it difficult to identify globally optimal configurations.

Second, there is an inherent trade-off between heat dissipation performance and flow resistance. Most enhancement measures—such as adding turbulators, reducing channel width, or introducing wavy shapes—significantly increase pressure drop while improving the heat transfer coefficient [68,79]. Systematic theoretical guidance on achieving a Pareto optimal trade-off between these two aspects is still lacking. This trade-off is most critical for rib-enhanced and wavy channels, where the very mechanisms that enhance heat transfer (disrupting boundary layers, inducing secondary flows) inherently increase flow resistance; the pressure-drop penalty is particularly severe in wavy channels due to continuous flow redirection and Dean vortex generation, and in rib-enhanced channels due to form drag and flow blockage.

Third, numerical simulations dominate the field, while experimental validation is relatively insufficient. In some studies on conventional channel configurations, the work relies only on correlation-based validation or literature data without conducting independent prototype experiments. The effects of fabrication tolerances, contact thermal resistance, sealing, and other practical factors have not been fully evaluated.

This limitation applies across all channel types, but its consequences vary: for parallel channels, fabrication tolerances can significantly alter flow distribution among branches; for serpentine and wavy channels, the long and complex flow paths make pressure-drop predictions particularly sensitive to surface roughness and manufacturing precision; for double-layer channels, the additional sealing interfaces and assembly complexities introduce further uncertainties that are rarely addressed in numerical-only studies.

Fourth, most studies are tailored to specific battery types and discharge rate conditions. The generalizability of the optimization conclusions remains to be verified [68,80]. For example, it is unclear whether a channel structure optimized for high-rate conditions such as 5C or 6C would also perform well under normal 1C–3C operating conditions. Systematic comparisons addressing this question are still lacking. This limitation is especially relevant for serpentine and wavy channels, whose performance is highly dependent on flow velocity—their heat transfer enhancement mechanisms rely on sufficient momentum to generate secondary flows or boundary-layer disruption, which may diminish at lower flow rates; for double-layer channels, the optimal layer configuration and flow direction may differ between high-rate and low-rate conditions, yet few studies have systematically explored such cross-condition adaptability.

7 Bionic and Fractal Channel Design

7.1 Theoretical Basis

The core idea of bionic channel design is to draw inspiration from the optimized configurations of natural biological structures—such as leaf veins, tree roots, spider webs, and honeycombs—for material transport and energy exchange, and to apply these configurations to liquid cooling plate channel design. Natural branching networks, shaped by long-term evolution, possess characteristics such as high transport efficiency, low flow resistance, and uniform spatial distribution. These features provide rich topological templates for artificial channel design. Fractal theory provides the mathematical tools for the geometric description and performance characterization of bionic channels. The self-similarity and fractal dimension of branching networks can be used to quantify the space-filling capability and transport efficiency of the channels.

7.2 Typical Bionic Channels

7.2.1 Leaf Vein/Tree-Like Networks

Leaf vein and tree-root networks are among the most extensively studied bionic configurations for LCPs. Their common structural features include one or more main channels that distribute coolant to multiple levels of branching sub-channels, often with additional cross-connections between branches. This hierarchical architecture serves two complementary functions: the main channels ensure rapid coolant delivery across the plate, while the branching network distributes flow evenly over the heat-transfer surface. Designs within this category vary in complexity—from relatively simple tree-root patterns with limited branch levels to highly intricate leaf-vein networks with dense interconnections. A recurring design principle is that placing enhanced heat-transfer structures in the middle-to-rear region, rather than uniformly across the entire plate, can effectively balance thermal performance and flow resistance by allocating cooling capacity where the thermal boundary layer has fully developed.

The reported advantages of leaf-vein and tree-root designs are broadly consistent across studies: improved temperature uniformity, reduced pressure drop relative to serpentine channels, and better suppression of localized hot spots, particularly near electrode tabs. However, several critical limitations temper these claims. The performance gains are highly sensitive to geometric parameters such as branch angles, channel widths, and branching density, yet the optimal parameter sets vary considerably across studies due to differences in plate size, heat load, and flow conditions—making it difficult to extract universally applicable design

rules. Furthermore, the most intricate designs, while thermally superior, pose significant manufacturing challenges and are rarely evaluated against the best-performing conventional configurations (e.g., optimized serpentine or multi-pass channels) under identical boundary conditions. Nevertheless, when compared with simple straight or baseline serpentine designs under fair operating conditions, leaf-vein and tree-root channels consistently demonstrate superior temperature uniformity and lower pumping power requirements, confirming their overall advantage over traditional configurations, provided that manufacturing complexity and operating conditions are carefully considered in the design phase [81–83].

The overall channel architecture of a representative leaf-vein/tree-root bionic cooling plate is depicted in Fig. 9, with the key geometric parameters annotated in Fig. 10.

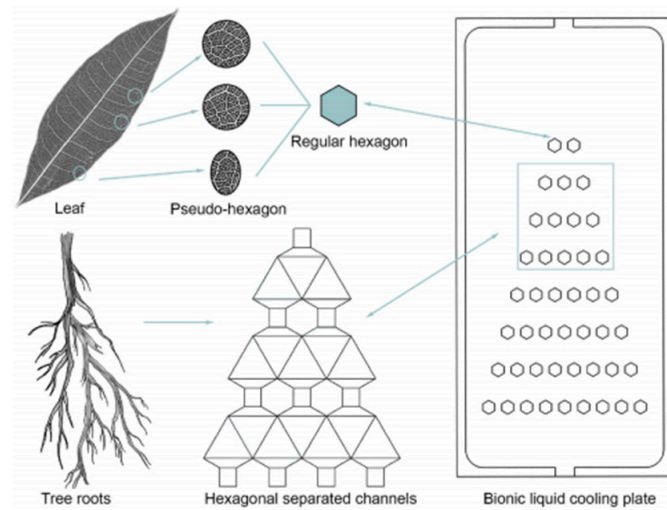


Figure 9: Design of leaf vein/tree root bionic liquid cooling plate [47].

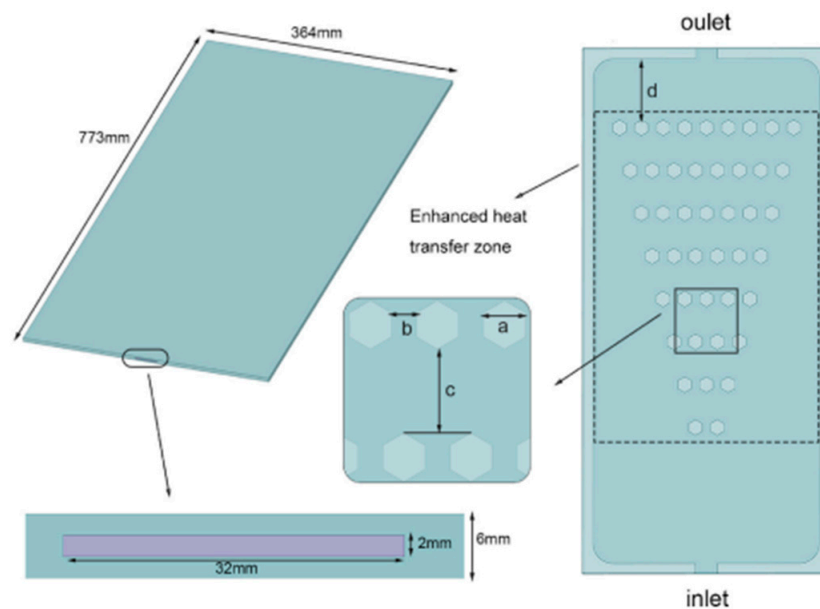


Figure 10: Geometric parameters of leaf vein/tree root bionic cooling plate [47].

7.2.2 Spider-Web/Honeycomb Structures

Spider-web and honeycomb configurations represent a distinct category of bionic channels characterized by high spatial symmetry and dense, interconnected flow networks. The spider-web structure consists of radial channels emanating from a central inlet to multiple concentric rings, creating a highly symmetric flow distribution pattern that naturally promotes uniform coolant delivery across the entire cold plate. This radial symmetry ensures that all regions of the battery receive comparable cooling, effectively suppressing localized hot spots. The honeycomb structure, by contrast, employs a dense array of regular hexagonal cells, which maximizes the heat transfer area by allowing each aluminum block to exchange heat with coolant through multiple surrounding surfaces. This configuration is particularly effective for large-format batteries where high heat flux needs to be dissipated uniformly across the plate.

The reported advantages of spider-web and honeycomb designs are consistently linked to their symmetrical and space-filling topologies. Both configurations achieve superior temperature uniformity compared to conventional serpentine or parallel straight channels, as the flow distribution is inherently more balanced. The spider-web design is particularly well-suited for high-rate discharge applications where rapid heat removal is required, while the honeycomb structure excels in applications demanding maximum heat transfer area within a constrained footprint. However, both configurations face significant manufacturing challenges: the intricate channel networks require advanced fabrication techniques (e.g., precision machining or additive manufacturing), which increase cost and limit scalability. Furthermore, the optimal geometric parameters are highly dependent on specific operating conditions, and designs optimized for one discharge rate may not perform equally well under other conditions. Despite these limitations, the spider-web and honeycomb channels consistently demonstrate superior temperature uniformity and lower flow resistance compared to conventional designs when evaluated under comparable operating conditions, confirming their overall advantage for battery thermal management applications, provided that manufacturing constraints and condition-specific optimization are carefully addressed.

The representative designs of these two bionic configurations are illustrated in Fig. 11 (spider-web) and Fig. 12 (honeycomb), respectively.

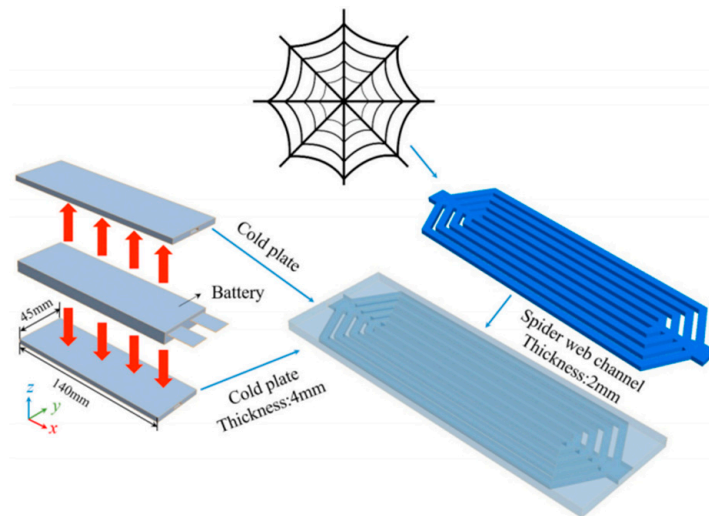


Figure 11: Representative figures of spider-web bionic cooling plate [48].

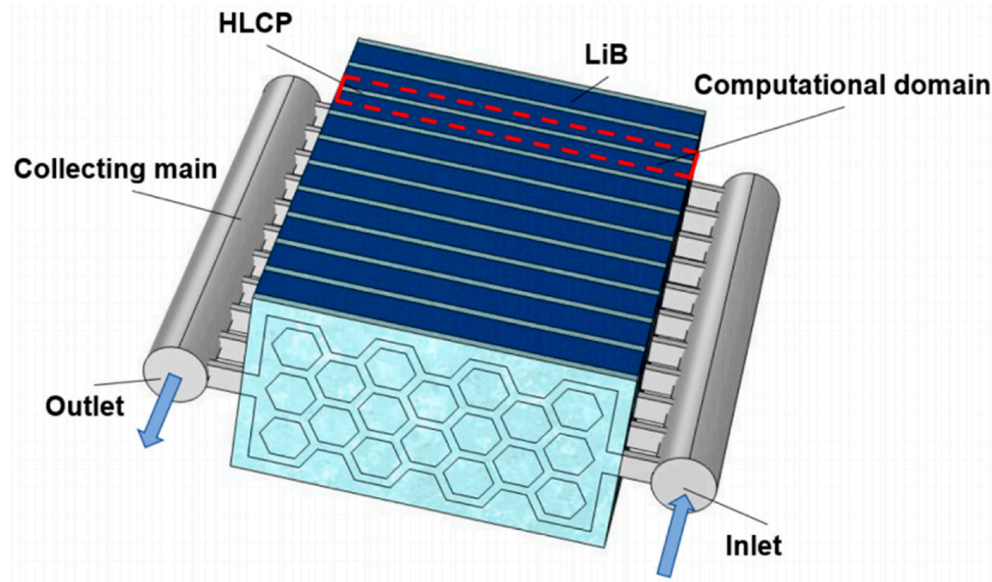


Figure 12: Representative figures of honeycomb bionic cooling plate [84].

7.2.3 Fish-Bone/Wing-Vein and Other Bionic Configurations

Fish-bone and wing-vein configurations represent a distinct category of bionic designs characterized by a central main channel from which multiple lateral branches extend at specific angles, resembling the structural patterns found in biological transport networks. The fish-bone design typically employs a single straight or serpentine main channel with symmetrically arranged branch channels along its length, where the branch angles and spacing are key parameters governing flow distribution and heat transfer. The wing-vein design, inspired by the venation patterns of insect wings, incorporates more complex multi-level branching units—typically consisting of sub-channels and side channels—that create a hierarchical flow network. Both configurations share a common design logic: the main channel ensures rapid coolant delivery across the plate, while the branching network distributes flow laterally to enhance coverage and disrupt thermal boundary layers. The fish-bone structure is particularly effective for large-format prismatic batteries where uniform cooling across a wide surface is required, whereas the wing-vein design excels in mitigating localized heat accumulation in the central regions of battery modules through its more intricate branching architecture.

Other bionic configurations, such as wavy channels inspired by natural waveforms and spiral-serpentine structures combining parallel and serpentine features, have also been explored. Wavy channels introduce periodic flow redirection that enhances fluid mixing and boundary-layer disruption, offering thermal performance intermediate between serpentine and parallel designs. Spiral-serpentine configurations aim to balance the long flow path of serpentine channels with the low resistance of parallel layouts. A critical comparison across these diverse bionic designs reveals a consistent trend: they uniformly outperform their conventional counterparts in temperature uniformity, though the degree of pressure-drop penalty varies considerably with geometric complexity. However, several cross-cutting limitations persist across all bionic configurations. Most studies are confined to single operating conditions and specific battery form factors, leaving the generalizability of optimized designs largely unverified. Manufacturing complexity and cost remain significant barriers to industrial adoption, particularly for intricate three-dimensional topologies. Moreover, the absence of standardized performance metrics makes direct quantitative comparisons across different bionic designs challenging. Despite these limitations, the collective evidence confirms that bionic

channels offer demonstrable advantages over conventional straight or serpentine designs in terms of temperature uniformity and overall thermal-hydraulic performance, provided that careful consideration is given to application-specific requirements, operating conditions, and manufacturing feasibility [85,86].

The geometric layouts of these two bionic channel designs are presented in Fig. 13 (fish-bone) and Fig. 14 (wing-vein), respectively.

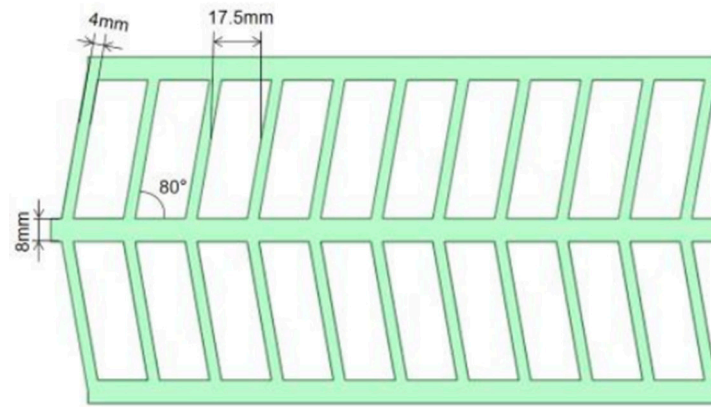


Figure 13: Representative figures of fishbone bionic cooling plate [80].

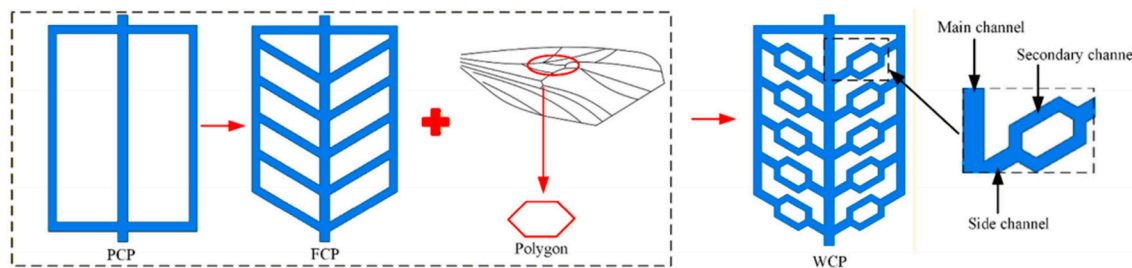


Figure 14: Representative figures of wing-vein bionic cooling plate [87].

7.3 Summary

Overall, bionic channels exhibit clear advantages over conventional configurations in thermo-hydraulic performance. First, branching structures can effectively increase the heat transfer area and improve temperature uniformity. Second, the flow resistance of bionic channels is generally lower than that of serpentine channels with comparable heat transfer capacity. This is because flow division reduces local velocities and vortex losses. Third, multi-level branching enables rational spatial allocation of cooling capacity, helping to alleviate hot spots. However, the engineering application of bionic channels still faces challenges in manufacturing feasibility and adaptability to multiple operating conditions.

8 Topology Optimization Flow Channel Generation

8.1 Basic Concepts and Mathematical Foundations

Topology optimization is a structural design method that does not rely on an initial configuration. It achieves maximum target performance by optimizing material distribution within a given design domain. In liquid cooling plate design, topology optimization treats the solid/fluid distribution of the channels as design variables. The objectives are typically to maximize heat transfer and/or minimize fluid dissipation. This approach automatically generates non-intuitive, high-performance channel configurations within the

design domain. Unlike parametric optimization, topology optimization is not limited to local adjustments of existing channel shapes. Instead, it explores the optimal channel topology globally, offering greater potential for innovation.

Mathematically, topology optimization for LCPs is commonly based on the variable density method. In this method, the material density of each element within the design domain (continuously varying between 0 and 1) is used as the design variable. Intermediate densities are penalized to drive the final configuration toward a 0/1 binary distribution. The governing equations include the Navier-Stokes equations with Darcy interpolation and the energy conservation equation. The objective function is often formulated as a weighted sum of maximizing heat transfer and minimizing fluid dissipation [88–90].

8.2 Typical Workflow

A typical topology optimization workflow includes the following steps: (1) Define the design domain, boundary conditions, and objective function. (2) Discretize the governing equations using finite element or finite volume methods. (3) Use material density as the design variable and solve iteratively through gradient-based optimization algorithms, such as the optimality criteria method, the method of moving asymptotes, or sequential quadratic programming. (4) Post-process the optimized density field (threshold segmentation, smoothing filtering) to extract the channel geometry contour. (5) Extrude the two-dimensional topological configuration into a three-dimensional model and perform CFD validation.

The post-processing of topology-optimized density fields into manufacturable 3D geometries involves a series of critical steps. First, density-field threshold segmentation is applied to distinguish fluid from solid regions—typically using a threshold value of 0.5, where elements above this value are identified as fluid channels. Second, contour extraction and curve fitting are performed to obtain smooth channel boundaries from the binary density distribution; spline interpolation is commonly employed to eliminate jagged artifacts and generate continuous channel profiles. Third, boundary smoothing is implemented through filtering or morphological operations to further reduce localized irregularities that could otherwise compromise flow performance or induce stress concentrations. Fourth, minimum feature-size constraints must be considered to ensure manufacturability; channels narrower than the fabrication limit (typically 0.5–1 mm for conventional machining, or 0.1–0.2 mm for additive manufacturing) should be eliminated or widened to meet the selected manufacturing process capabilities. Finally, the optimized 2D channel layout is extruded into a 3D solid model with prescribed channel height (typically 2–3 mm), and inlet/outlet manifolds are added to facilitate integration with external cooling circuits. These post-processing steps bridge the gap between mathematical optimization and engineering fabrication, ensuring that the theoretically optimal topology can be physically realized without compromising its performance advantages.

Zhan et al. [91] demonstrated the effectiveness of this approach by using bionic leaf-vein channels as the initial solution for topology optimization. After obtaining the optimized density field, they applied threshold segmentation and spline smoothing to extract the channel contour, then extruded the 2D configuration into a 3D model for CFD validation. The optimized configuration, when compared with traditional S-shaped channels, achieved a significant reduction in pressure drop while maintaining comparable thermal performance. The topology optimization process using the two initial solution strategies, along with their iterative convergence behavior, is illustrated in Fig. 15. This study also revealed that increasing the weight coefficient for heat transfer leads to denser channel branches and more uniform temperature distribution, whereas increasing the weight for fluid dissipation results in simpler, wider channels with lower pressure drop. Similar topology optimization strategies have been extended to various battery formats and cooling conditions, demonstrating broad applicability [92–97].

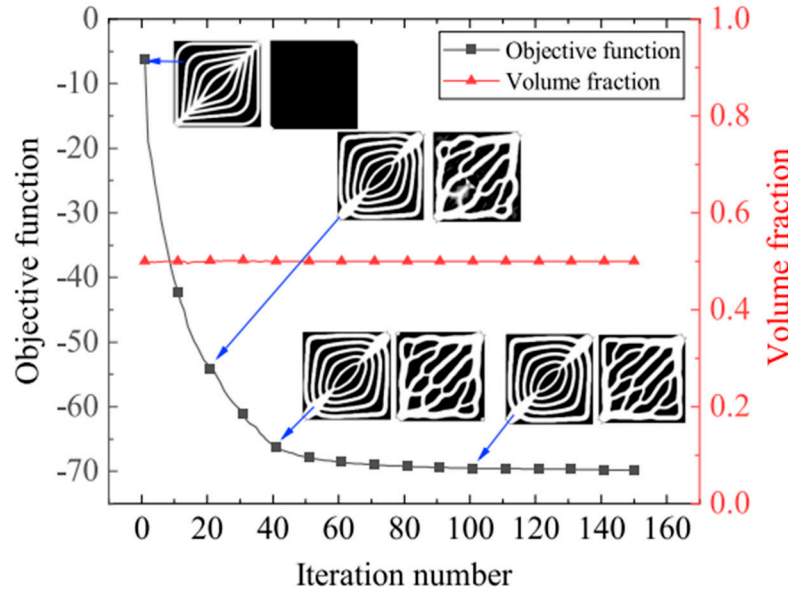


Figure 15: Two initial solution topology optimisation processes with iterative convergence curves for objective functions [91].

8.3 Numerical Treatment Techniques

Key numerical treatment techniques in topology optimization include: (1) density filtering and projection, used to control the minimum feature size and eliminate checkerboard patterns; (2) Darcy interpolation, used to distinguish between solid regions (low permeability) and fluid regions (high permeability); (3) volume fraction constraints, used to control the proportion of the channel area within the design domain; and (4) multiple initial solution strategies, used to avoid being trapped in local optima.

8.4 Advantages and Challenges of the Method

Topology optimization offers significant advantages over conventional design methods. First, it does not require a pre-defined channel configuration, allowing the algorithm to freely generate the optimal topology within the design domain and thus break through the performance limitations of traditional configurations as demonstrated in recent LCP topology optimization studies [93,94]. Second, it naturally supports multi-objective trade-offs. The Pareto frontier between thermal performance and flow resistance can be systematically explored by adjusting the weight coefficients, with studies showing that increasing the heat-transfer weight yields denser channel branches and more uniform temperature distributions, whereas increasing the flow-dissipation weight produces simpler, wider channels with lower pressure drop [88,97]. Third, it can be integrated with heuristic methods such as bionic design. Using a bionic configuration as the initial solution accelerates convergence and improves the final performance; for example, Zhan et al. [91] demonstrated that topology optimization initialized with a leaf-vein bionic channel achieved superior thermal performance compared to uniform-density initialization.

However, topology optimization still faces several challenges in LCP design. First, most current studies perform two-dimensional topology optimization and then directly extrude the configuration into a three-dimensional model as in the majority of recent designs [94,96]. This approach does not account for three-dimensional flow effects or thickness-wise heat transfer variations, which may sacrifice some performance potential. Second, numerical simulations still dominate, while experimental validation is limited; although a few recent studies have conducted experimental validations on topology-optimized prototypes, the vast

majority of designs remain at the purely numerical stage, and the optimized designs are rarely validated under off-design conditions, leaving their robustness across varying operating conditions largely unverified, as noted in the limitations of existing topology optimization studies [94,95]. Third, topology-optimized channels often feature complex and irregular geometries that pose significant manufacturing challenges. The intricate branching networks and curved channel profiles are difficult to realize with conventional machining; while additive manufacturing offers greater geometric freedom, it introduces constraints such as minimum feature size, overhang angle limitations, and surface roughness considerations that affect both flow performance and structural integrity. Moreover, the post-processing steps required to extract manufacturable geometries from density fields—including smoothing and feature extraction—may compromise the theoretical performance advantages of the optimized designs; as noted by Lin et al. [96], the streamlined solid blocks in topology-optimized channels require individual machining codes for each contour, significantly increasing manufacturing complexity and cost. These fabrication barriers substantially increase production costs and limit scalability, creating a significant gap between laboratory-optimized designs and industrial implementation. Fourth, the selection of weights for the optimization objectives is mostly based on parametric sweeps rather than on actual system-level energy economy; studies have shown that the optimal weights vary with operating conditions, and different weight assignments lead to fundamentally different channel topologies [97,98]. Moreover, few studies have systematically quantified how uncertainties in boundary conditions or material properties affect the robustness of the optimized performance, with most weight selections relying on engineering experience rather than objective optimization criteria [98].

9 Intelligent Algorithms and Multi-Objective Optimization

9.1 Formulation of the Multi-Objective Optimization Problem and Surrogate Model Methods

The optimization design of liquid cooling plates is inherently a multi-objective problem, requiring trade-offs between thermal performance (e.g., reducing maximum temperature and temperature difference) and flow performance (e.g., reducing pressure drop and pumping power). However, the computational expense of high-fidelity CFD simulations makes direct integration with iterative optimization impractical. Surrogate model methods—also known as metamodels or response surface models—address this challenge by constructing approximate models from a limited set of simulation data, significantly reducing optimization cost while maintaining acceptable accuracy.

A critical examination of the surrogate-model literature reveals a recurring pattern: studies consistently report high predictive accuracy (R^2 typically > 0.95) for RSM, GP/Kriging, and ANN-based models, yet the sample sizes used—often 30 to 50 CFD runs—are generally insufficient to construct reliable surrogates for highly nonlinear thermal-fluidic responses, raising concerns about overfitting and limited predictive robustness. A common limitation across studies is that model validation is frequently performed using only training data or limited cross-validation, without independent experimental verification of the optimized designs [99,100], which undermines confidence in reported outcomes. Looking forward, the integration of machine learning into LCP optimization presents several promising directions. Deep neural networks have demonstrated the ability to reduce computational cost by approximately 95% [101,102], while active learning strategies and physics-informed neural networks (PINNs) offer the potential to further reduce training data requirements by embedding governing equations into the learning process. However, critical challenges remain unresolved: the lack of standardized benchmarking datasets and validation protocols prevents fair comparison of different surrogate-model approaches; the gap between simulation-based optimization and real-world performance—due to unmodeled factors such as manufacturing tolerances, contact thermal resistance, and coolant degradation—remains largely unaddressed; and the computational expense of high-fidelity

simulations continues to limit the adoption of data-intensive deep learning methods in routine engineering practice. Addressing these challenges requires closer collaboration between the CFD, machine learning, and battery thermal management communities to develop robust, generalizable, and practically deployable optimization frameworks. Table 8 provides a systematic comparison of representative alternative modeling methods, including their sample sizes, validation methods, reported prediction accuracy, and constraints.

Table 8: Comparison of surrogate modeling approaches in LCP optimization.

Surrogate Model Type	Sample Size	Validation Method	Prediction Accuracy	Constraints	Final Verification
RSM/RSA	16–40	ANOVA, R^2	$R^2 > 0.92$	Variable ranges; volume fraction	CFD; some with experiment
GP/Kriging	150–200	R^2 , RMSE	R^2 up to 0.998	Variable ranges; $\Delta T/\Delta P$ constraints	CFD or FE simulation
ANN/BPNN	31–300	R^2 , correlation	R^2 up to 0.99988	Variable ranges	CFD + experimental verification
DNN	500	R^2 , MSE	$R^2 > 0.97$	Variable ranges	CFD + transient verification
RBF	40	Median/max error	Median error < 0.021 ; Max error < 0.051	Variable ranges	CFD (MDO framework)
CAwOA-BP	155	R^2 vs. standard BP	R^2 : 0.877 (Nu); 0.992 (f)	Variable ranges	CFD validation

Notes: RSM = Response Surface Methodology; RSA = Response Surface Approximation; GP = Gaussian Process; ANN = Artificial Neural Network; BPNN = Back-Propagation Neural Network; DNN = Deep Neural Network; RBF = Radial Basis Function; CAwOA-BP = Chaotic mapping and Adaptive weight Whale Optimization Algorithm optimized BP neural network; MDO = Multidisciplinary Design Optimization; R^2 = coefficient of determination; RMSE = Root Mean Square Error; MSE = Mean Squared Error; f = friction factor; Nu = Nusselt number; $T_{\max}$ = maximum temperature; ΔT = temperature difference; ΔP = pressure drop; FE = Finite Element.

9.2 Multi-Objective Optimization Algorithms

After the surrogate model is established, efficiently searching the design space and obtaining the optimal solution set becomes the core of multi-objective optimization. Genetic algorithms (GA) and their multi-objective version NSGA-II (Non-dominated Sorting Genetic Algorithm II) have become the most widely adopted optimization algorithms in BTMS multi-objective optimization. This is due to their strong global search capability and their advantage of not requiring gradient information.

NSGA-II maintains the diversity and distribution uniformity of Pareto front solutions through non-dominated sorting and crowding distance mechanisms. It can obtain a set of Pareto-optimal solutions in a single run, allowing designers to make flexible choices based on actual engineering preferences [98]. Fig. 16 illustrates the general workflow of NSGA-II.

Fig. 16 is not merely a generic algorithm flowchart; in LCP optimization studies, each step of the NSGA-II workflow maps directly to specific design decisions. Taking the bionic leaf-vein cold plate optimization by Zhan et al. [49] as an illustrative example, the algorithm is configured with four design variables—channel number n (8–14), branching angle α (90° – 150°), wing-channel width d (2.5–4 mm), and channel height h (2–5 mm)—which collectively define the channel geometry. The optimization seeks to minimize three conflicting objective functions: the maximum battery surface temperature $T_{\max}$, the pressure drop ΔP , and the temperature standard deviation T_σ (a measure of temperature uniformity). Rather than running expensive CFD simulations at each iteration, the study constructs response surface models (R^2 values of 0.995, 0.997, and 0.994 for the three objectives, respectively) to serve as surrogate models, enabling rapid fitness evaluations during NSGA-II iterations. Upon convergence, the algorithm yields a Pareto front of non-dominated solutions, from which the final design is selected by analyzing the distribution proportions of each design variable within the optimal solution set and using the Figure of Merit (FOM) as

a comprehensive performance indicator. This results in the optimal parameter combination: $n = 13$, $\alpha = 91^\circ$, $d = 3.8$ mm, and $h = 4$ mm. This example demonstrates how the generic NSGA-II flowchart in Fig. 16 is instantiated into concrete LCP optimization practice.

Several key challenges remain in current multi-objective optimization practices. The weighting coefficients used in weighted sum formulations are typically determined through parameter sweeps rather than systematic or adaptive methods; however, the optimal trade-off between thermal and flow objectives is inherently condition-dependent and varies with operating conditions and design constraints. The computational cost of generating sufficient high-fidelity CFD samples to build surrogate models remains high, particularly for high-dimensional problems, which limits the practical adoption of data-intensive methods. Furthermore, most optimization studies rely on the assumption of steady-state, uniform heat sources, neglecting the dynamic and non-uniform thermal behavior observed during actual battery operation. Validation is primarily numerical; experimental validation of optimized designs is the exception rather than the rule. Looking ahead, promising directions include adaptive weight adjustment strategies that respond to changing operating conditions, multi-fidelity surrogate modeling methods that balance accuracy and computational cost, and the integration of real-time thermal state prediction with online optimization of adaptive cooling control. Addressing these challenges is expected to require closer integration of optimization algorithms with experimentally validated physical models, as well as a shift from component-level optimization frameworks to system-level optimization frameworks.

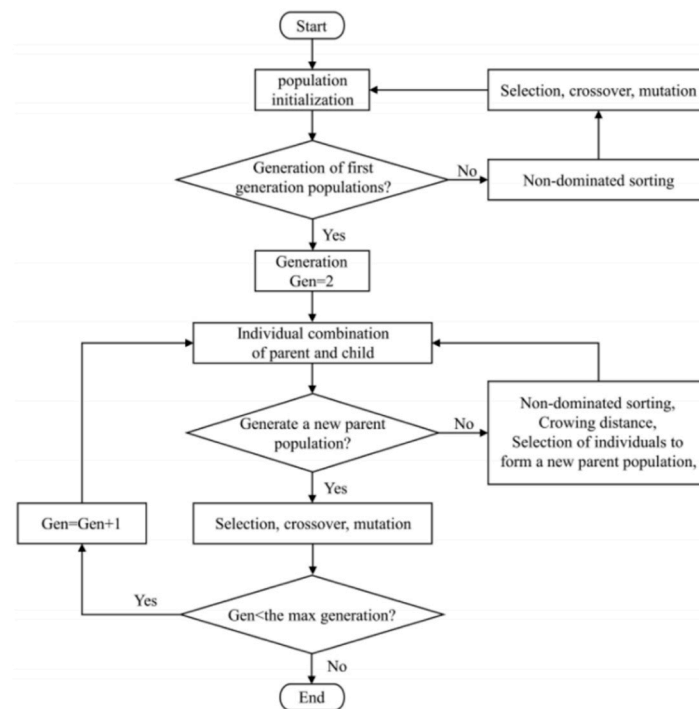


Figure 16: Flow of NSGA-II [49].

9.3 Integrated Optimization Framework and Engineering Applications

Current multi-objective optimization research for LCPs has evolved from isolated single-algorithm applications to systematic frameworks that integrate Design of Experiments, high-fidelity CFD simulation, surrogate model construction, and evolutionary-algorithm-based multi-objective optimization. In this workflow, space-filling sampling methods generate design points across the parameter space, CFD

simulations provide response data, surrogate models—ranging from RSM and GP/Kriging to ANN and its variants—are trained to replace expensive simulations, and Pareto-front solutions are obtained for final decision-making. This surrogate-assisted paradigm offers substantial computational advantages, reducing the required simulation count from tens of thousands to a few hundred while providing designers with a range of Pareto-optimal alternatives that avoid the bias of single weighting coefficients.

Despite these methodological advances, the practical deployment of these optimization frameworks faces several critical challenges that remain insufficiently addressed. The reliance on steady-state, uniform heat-source assumptions neglects the dynamic, SOC-dependent non-uniform thermal behavior during actual battery operation, limiting the real-world relevance of optimized designs. Experimental validation remains the exception rather than the rule, with most studies confined to single-cell simulations without accounting for cell-to-cell thermal crosstalk or the influence of clamping pressure on contact thermal resistance. The computational cost of generating sufficient CFD samples for high-dimensional problems still hinders real-time optimization, and the robustness of surrogate-model predictions under off-design conditions or input uncertainties is rarely quantified. Looking forward, addressing these gaps will require closer integration of experimentally validated physical models with optimization algorithms, multi-fidelity approaches to balance accuracy and cost, system-level rather than component-level optimization, and explicit consideration of manufacturability and operational variability.

9.4 Methodological Summary and Design Implications

First, the choice of surrogate model should match the characteristics of the problem. For problems with few design variables (≤ 5) and relatively smooth response surfaces, RSM or RSA is sufficiently accurate and computationally most efficient. For medium-scale problems, GP/Kriging generally offers the best balance between accuracy and cost. For problems with many variables or strong nonlinearity, ANN and its improved variants (e.g., CAwOA-BP) have stronger fitting capabilities. However, care must be taken to avoid overfitting and to ensure an adequate number of training samples.

Second, the multi-objective optimization algorithm and the decision-making method should be co-designed. NSGA-II is currently the mainstream algorithm for BTMS multi-objective optimization, offering good convergence and well-distributed Pareto fronts. Subsequent decision-making from the Pareto front can be performed using objective multi-criteria methods such as TOPSIS, or through subjective selection based on engineering constraints. The MDF architecture proposed by Wang et al. [103], which decomposes the BTMS into multiple disciplinary sub-problems for collaborative optimization, offers a new approach for system-level BTMS optimization.

Third, the computational advantage of surrogate-assisted optimization is significant. The work of Mansour et al. [101] showed that DNN-assisted GA optimization can reduce computational cost by approximately 95%. Ye et al. [104], after constructing a BPNN with 300 samples, performed the entire NSGA-II optimization based solely on surrogate model predictions, completely avoiding repeated CFD simulations during the iterative optimization process. This provides a feasible pathway for industry to conduct systematic parametric optimization within product development cycles.

Finally, experimental validation remains indispensable. Although the surrogate model–intelligent algorithm framework has demonstrated good optimization effectiveness at the simulation level, the simulation models themselves are based on several idealized assumptions (e.g., uniform heat source, neglect of contact thermal resistance, laminar flow assumption). The actual cooling performance of the optimized design must be verified through experimental platforms. Some studies [104,105] have conducted corresponding experimental validations, with validation errors generally well controlled (temperature error < 3.8%, pressure

drop error < 4.18% [106]), which further enhances the credibility of the optimization methods. However, most topology optimization studies remain at the purely numerical stage, and the coverage of experimental validation urgently needs to be expanded.

10 Summary and Outlook

This review systematically examines recent advances in LCP optimization design, covering conventional channel configurations, bionic/fractal designs, topology-optimized channel generation, and surrogate-model-assisted multi-objective optimization. The field has evolved into a complete technical chain encompassing mechanism understanding, simulation evaluation, configuration innovation, and intelligent optimization.

Several key findings emerge from this synthesis. First, channel geometry and layout remain the most influential design parameters, with heat transfer enhancement fundamentally relying on thermal boundary layer disruption and secondary flow generation. Second, bionic channels (leaf-vein, spider-web, honeycomb, fish-bone, and wing-vein configurations) consistently demonstrate superior temperature uniformity and lower flow resistance compared to conventional serpentine designs, though performance gains are highly sensitive to geometric parameters and operating conditions. Third, topology optimization, particularly when initialized with bionic structures, can generate non-intuitive, high-performance channel geometries that achieve overall performance improvements exceeding 90% and pressure-drop reductions over 70% in some studies. Fourth, surrogate-model-assisted optimization frameworks—employing RSM, GP/Kriging, ANN, and their variants—have become the dominant paradigm for addressing multi-objective conflicts, enabling efficient Pareto-front exploration with only hundreds of CFD samples instead of tens of thousands.

Despite these advances, several common challenges persist. Numerical simulations overwhelmingly dominate the literature, while experimental validation—particularly for complex bionic and topology-optimized geometries—remains insufficient. Most studies are tailored to single battery types, fixed discharge rates, and specific operating conditions, leaving the generalizability and robustness of optimized designs largely unverified. LCP optimization is predominantly conducted at the component level, lacking integration with battery aging characteristics, cell-to-cell thermal crosstalk, and vehicle-level thermal management systems. Furthermore, manufacturability constraints and cost implications of increasingly complex channel geometries are rarely addressed, creating a significant gap between academic research and industrial application.

Future LCP optimization design is moving toward intelligence, systematization, and full-life-cycle consideration. In terms of intelligence, machine learning-based surrogate models, physics-informed neural networks, and reinforcement learning for real-time thermal state prediction and adaptive cooling control offer promising pathways to further reduce computational costs and enable online optimization. In terms of systematization, LCP design must expand beyond single-component optimization to incorporate battery aging effects, extreme fast charging transients, and coupling with vehicle-level thermal loops [107]. In terms of full-life-cycle consideration, performance evaluation frameworks should cover the entire chain from design and manufacturing to operation, aging, and maintenance, accounting for time-dependent factors such as contact thermal resistance evolution and coolant degradation. Furthermore, cross-fertilization with adjacent energy-device disciplines offers additional opportunities for innovation. Strategies such as hydrogel electrolyte engineering for flexible zinc-air batteries [108], Cu-based nanoarray catalysts for electrochemical CO₂ reduction [109], and polydopamine-mediated surface functionalization for electroless deposition [110] may inspire novel LCP surface coatings, anti-corrosion treatments, and bio-inspired channel designs that enhance both thermal performance and long-term durability. These interdisciplinary insights, combined

with the intelligent and systematic optimization frameworks discussed above, will further accelerate the transition of LCP technology from laboratory research to industrial-scale deployment.

Practical recommendations for future research include: (1) validating simulation-based optimization results with module-level or pack-level experiments rather than single-cell-only tests; (2) establishing closed-loop “design–fabrication–testing” workflows with explicit reporting of manufacturing methods, tolerances, and sealing solutions; (3) incorporating battery aging models into objective functions to enable life-cycle-aware thermal management; and (4) developing standardized benchmarking datasets and validation protocols to enable fair comparison of different optimization approaches. LCP optimization design is now at a critical transition point—shifting from experience-driven to data-intelligent-driven approaches, and from isolated component optimization to system-level collaborative optimization. Multidisciplinary integration is expected to be the core driving force for sustained breakthroughs in this field.

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