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A Review of Structural Optimization Methods for Electric Vehicle Battery Cooling Systems

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Abstract
The geometry of a battery cooling system has a direct influence on cell temperature, temperature uniformity, pressure loss, and the energy required to circulate the coolant. This review examines recent approaches used to optimize liquid-cooled structures for electric vehicle battery packs, with particular attention to channel layout, manifold configuration, contact geometry, and plate dimensions. Parametric studies remain useful for identifying influential variables and explaining the physical behavior of a design. For problems involving several interacting parameters, multi-objective algorithms and surrogate models provide a more practical alternative to repeated high-cost CFD simulations. Recent studies also show growing interest in bio-inspired channels and topology optimization, which can generate unconventional flow paths but often introduce manufacturing and validation difficulties. Across the reviewed work, the most reliable designs are those evaluated against both thermal and hydraulic criteria and subsequently rechecked using the original numerical model or experiments. Based on these findings, a structured design procedure is discussed, covering problem definition, variable screening, numerical validation, sampling, surrogate construction, Pareto optimization, and final verification. Future research should place greater emphasis on robust designs that remain effective under changing operating conditions and can be manufactured and integrated at module or pack level.

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1. Introduction

Lithium-ion batteries combine high energy density, favorable power capability, and long cycle life, but their electrochemical performance and safety remain strongly temperature dependent. Excessive temperature accelerates aging and can intensify thermal-runaway risk, whereas large temperature differences among cells create non-uniform current distribution and uneven degradation. Reviews of battery thermal management consistently identify liquid cooling as one of the most effective options for high-power electric vehicles because it provides a high heat-transfer coefficient and a compact integration route [1, 3, 6]. The design problem, however, is not solved by selecting a coolant alone. The cold-plate structure governs how the coolant is distributed, where local heat is removed, how much pumping power is required, and whether the component can be manufactured, sealed, and integrated into a battery module.

Battery-pack design has therefore shifted from selecting a cooling architecture to optimizing its internal geometry. Packaging reviews have emphasized that cell arrangement, cooling contact area, module spacing, and pack-level flow distribution are coupled design decisions [7, 8]. Comparative studies between air and liquid cooling, and among alternative liquid-cooling structures, show that improved temperature uniformity is often obtained at the expense of pressure drop, complexity, or mass [9, 12]. This trade-off explains why structural optimization must be formulated as a multi-objective problem rather than as a search for the minimum temperature alone.

The structural design space is broad. Conventional plates employ straight, parallel, U-shaped, or serpentine channels. More advanced configurations use splitters, gradient contact surfaces, cellular jackets, mini-channels, manifolds, ribs, pin-fin features, or branched bio-inspired networks [13, 24]. In each case, the thermal-hydraulic response depends on channel width and height, hydraulic diameter, channel number, wall thickness, flow-path length, turning radius, inlet and outlet placement, contact angle, and the distribution of solid material around the cells. These variables interact nonlinearly. A small channel may increase local convection but also raise friction loss. A larger contact area can reduce cell temperature but increase plate mass. Additional branches can improve distribution but create recirculation zones or manufacturing difficulty.

Optimization methods have evolved in parallel with the structural complexity. Early studies commonly changed one factor at a time or used limited parametric sweeps. Design-of-experiments methods later enabled simultaneous assessment of several variables. Metaheuristic algorithms then became attractive because they can search nonlinear and discontinuous design spaces without requiring analytical gradients. More recently, computational-fluid-dynamics models have been combined with Gaussian-process regression, neural networks, and other surrogate models to reduce optimization cost [31, 36, 43]. Topology optimization and bio-inspired design have further expanded the search space beyond predefined channel families [30, 32, 35, 44]. Recent studies have progressively moved from comparative geometric analysis to surrogate-assisted multi-objective optimization of serpentine and mini-channel cooling structures [18,31,36,40].

This paper reviews structural optimization methods for electric vehicle battery cooling systems, with emphasis on cooling-structure design, thermal and hydraulic performance, optimization techniques, and model validation. Section 2 presents the main structural configurations and performance criteria. Section 3 compares the commonly used optimization methods. Section 4 discusses the main findings, remaining limitations, and future research directions. Section 5 summarizes the principal conclusions.

2. Structural Design Space and Performance Criteria

2.1. Cooling-structure families

Parallel-channel plates are attractive because they offer short flow paths and relatively low pressure loss. Their principal weakness is maldistribution. Coolant tends to favor low-resistance branches, particularly when the inlet manifold is compact or the channels are not hydraulically balanced. The resulting flow non-uniformity can produce local hot spots even when the average coolant flow rate is sufficient. Splitter design and manifold geometry are therefore as important as the channel dimensions themselves [16, 25].

Serpentine channels force the coolant through a continuous path and can provide consistent contact with successive cells. They are simple to seal and are widely used as a baseline for optimization. Their disadvantage is cumulative pressure loss along the flow path and a progressive coolant-temperature rise. Studies on parallel-spiral, tailored, and enhanced serpentine plates show that turning geometry, branch connection, local width, and path length can be modified to improve the thermal-hydraulic compromise [23, 27, 29, 37]. The geometry-driven work in [31] further demonstrated that wall thickness and channel thickness can be more influential than a visually prominent angle parameter.

Mini-channel and multi-channel cold plates increase heat-transfer area while maintaining a compact thickness. They are suitable when the plate must remove high heat flux from prismatic or densely packed modules. Their performance is sensitive to the number of channels, hydraulic diameter, spacing, plate thickness, and manifold design [24, 36, 41]. The gain in temperature control can be offset by higher pumping power and stronger sensitivity to manufacturing tolerance or blockage. Structural optimization should therefore include hydraulic constraints from the beginning rather than treating pressure drop as a secondary check.

Table 1: Main structural families used in liquid-cooled EV battery thermal management systems.

Structure	Key variables	Engineering implication
Parallel/manifold	Channel number, width, manifold taper, inlet position	Low pressure loss, but sensitive to flow maldistribution
Serpentine	Path length, turns, thickness, contact area	Simple sealing and coverage, but cumulative pressure loss
Mini-channel	Hydraulic diameter, spacing, plate thickness	High heat-transfer area, but tolerance and pumping sensitivity
Jacket/cellular	Contact pattern, jacket thickness, cell spacing	Large contact area, but assembly and mass penalties
Bionic/topology	Branching law, density field, minimum feature size	Large design freedom, but manufacturing and validation challenges

Jacket, cellular, and modular structures surround cylindrical cells or place cooling passages near a large fraction of the cell surface. These layouts can improve circumferential heat removal and reduce localized thermal gradients [15, 19]. Compact and lightweight solutions have also been proposed for cylindrical packs [17]. Their key design questions are the contact pattern, cell-to-coolant distance, structural mass, assembly method, and the ability to accommodate cell expansion and service requirements.

Bio-inspired and topology-optimized plates seek flow paths that are not limited to conventional straight or serpentine templates. Fishbone, honeycomb, branching, and other bionic patterns aim to distribute flow more uniformly while maintaining short heat paths [30, 32, 33]. Topology optimization can create still more unconventional solid-fluid layouts [34, 35, 44]. These methods are promising, but their practical value depends on whether the optimized features can be manufactured, cleaned, sealed, and verified under realistic operating conditions.

2.2. Geometric variables and physical mechanisms

Channel size controls both convective heat transfer and friction. Reducing hydraulic diameter can increase the local heat-transfer coefficient, but it also increases velocity and pressure loss for a fixed flow rate. Increasing channel height can reduce pressure drop but may move the coolant farther from the cell surface or increase plate thickness. The correct direction therefore depends on the imposed boundary condition. A design optimized at fixed inlet velocity may not remain optimal at fixed mass flow or fixed pump power. This distinction should be stated explicitly in every optimization study.

Wall thickness and contact geometry govern conduction from the cell to the coolant. Thin walls reduce conduction resistance but may weaken the plate and complicate welding or brazing. Thick walls improve stiffness and manufacturing tolerance but can increase thermal resistance and mass. Investigations of gradient contact angles, channel diameter, contact length, and cooling-block geometry show that the solid-side heat path can dominate the result even when the coolant-side layout appears unchanged [13, 18].

Inlet and outlet placement controls the global temperature field. A central inlet can improve symmetry, while edge inlets simplify pack integration. Multiple inlets reduce flow-path length but require additional manifolds and sealing interfaces. Flow reversals and repeated bends increase mixing, yet they can also create separation and dead zones. Ribs and V-shaped features have been used to disturb the boundary layer and redistribute coolant [28]. Such features should be optimized together with Reynolds number and minimum manufacturable size rather than inserted as isolated enhancements.

The cell-to-plate interface is another structural variable. Contact area, thermal-interface material thickness, clamping pressure, and local flatness affect the effective thermal resistance. A numerically optimized channel cannot compensate for a poorly defined interface. Structural optimization should therefore include realistic contact resistance or at least a sensitivity study. This is especially important when comparing pouch, prismatic, and cylindrical cells, whose heat-generation distribution and contact conditions differ [20, 21].

2.3. Objectives, constraints, and validation metrics

The most common thermal objectives are maximum cell temperature and maximum temperature difference. Maximum temperature is linked to safety and aging, whereas temperature difference is a practical measure of pack uniformity. Average temperature alone is not sufficient because it can conceal localized hot cells. The optimal structure should also be evaluated across time, not only at the final simulation instant, when the operating condition is transient.

Hydraulic objectives include pressure drop, pumping power, flow maldistribution, and sometimes coolant-volume or plate-mass penalties. Pressure drop is easy to report but does not directly represent auxiliary energy unless flow rate and pump efficiency are also specified. Pumping power provides a better system-level metric, but it should be calculated consistently. Structural optimization becomes more meaningful when the thermal objectives are considered together with pressure drop or pumping power [25, 38, 43].

Mechanical and manufacturing constraints are less frequently included, although they can eliminate many numerically attractive designs. Minimum wall thickness, maximum plate deformation, allowable stress, sealing length, tool access, channel curvature, minimum feature size, and leakage risk should be treated as constraints. Mass and volume are also important because a cooling structure that reduces temperature by adding substantial metal may reduce pack-level energy density.

Validation should occur at three levels. First, the numerical model should be checked for mesh independence, energy balance, and boundary-condition consistency. Second, the surrogate should be validated using unseen CFD points and uncertainty indicators. Third, selected designs should be tested experimentally, including temperature and pressure-drop measurements. Many published studies provide strong numerical optimization but limited full-system validation. This remains one of the main barriers to transferring optimized geometries to production.

3. Structural Optimization Methods

3.1. Parametric studies and design of experiments

One-factor-at-a-time studies remain useful in the early design stage. They provide clear physical interpretation and can reveal monotonic trends. Studies on channel diameter, contact length, splitter geometry, and mini-channel dimensions illustrate the value of this approach [16, 18, 24]. Its limitation is that interactions among variables are easily missed. When channel width, wall thickness, and inlet configuration interact, the best value of one variable depends on the settings of the others.

Design-of-experiments methods address this limitation by distributing samples across the design space. Full factorial designs are transparent but become expensive as the number of variables increases. Response-surface designs are efficient for low-order relationships, while Latin hypercube sampling provides better space-filling behavior for surrogate training. The sample size should be selected according to dimensionality, expected nonlinearity, and validation needs. A compact data set can be sufficient for a smooth three-variable problem, but it may be inadequate for topology, manifold, or multi-operating-condition optimization.

Sensitivity analysis is particularly valuable before optimization. It identifies variables that contribute little to the objectives and can reduce the search dimension. In the serpentine-channel study in [31], wall thickness was the dominant variable for both maximum temperature and temperature difference, while the contact-surface angle was less influential. Such information improves interpretability and helps prevent the optimizer from spending evaluations on weak variables.

3.2. Metaheuristic and multi-objective optimization

Battery-cooling design usually contains conflicting objectives and nonlinear constraints, making population-based metaheuristics a common choice. Genetic algorithms, particle-swarm methods, and related evolutionary techniques can search discontinuous spaces without gradient information. Their main advantage is flexibility. Their main disadvantage is the number of model evaluations required. Directly coupling a large population with three-dimensional CFD can be computationally prohibitive.

NSGA-II is widely used because it produces a Pareto set rather than a single weighted solution. This is appropriate when the designer must choose between temperature reduction and hydraulic cost. The Pareto front also exposes whether a small thermal improvement requires a disproportionately large pressure-drop penalty. Multi-objective studies on fast charging, serpentine systems, and general battery thermal management demonstrate the value of this approach [25, 38].

The optimization problem must nevertheless be formulated carefully. A Pareto front is only meaningful when the objectives use consistent boundary conditions and the constraints reflect the intended application. For example, optimizing temperature at fixed velocity while minimizing pressure drop can bias the result because the mass flow changes with channel area. More rigorous studies use fixed mass flow, fixed pump power, or explicit system constraints. Constraint handling should also include minimum dimensions and maximum allowable pressure drop.

3.3. Surrogate-assisted optimization and machine learning

Surrogate models reduce the computational burden by approximating the CFD response. Gaussian-process regression is attractive for small and medium data sets because it provides both a prediction and an uncertainty estimate. Polynomial response surfaces are simple and interpretable but can become inaccurate for highly nonlinear flow. Artificial neural networks and deep-learning models can represent complex relationships, although they generally require more training data and careful regularization.

Several recent studies have combined surrogates with multi-objective optimization. Surrogate-assisted serpentine optimization, machine-learning-based U-shaped designs, deep-learning-assisted sandwich plates, and hybrid-manifold optimization show the growing importance of data-driven design [37, 39, 42, 43]. The CFD–GPR–NSGA-II framework in [36] and the surrogate-assisted framework in [40] further demonstrate how training, cross-validation, Pareto search, and final CFD verification can be integrated into a single workflow.

A surrogate should not be judged by a high coefficient of determination alone. Error distribution, cross-validation, prediction intervals, and performance near the Pareto front are more important. The optimizer tends to exploit regions where the surrogate is overconfident. Adaptive sampling can reduce this risk by adding CFD points in regions with high uncertainty or high expected improvement. This is especially useful when the design space includes strong geometric interactions.

The selected Pareto designs must be re-evaluated using the original high-fidelity model. A surrogate-only optimum is not a final engineering result. The difference between surrogate prediction and CFD verification should be reported for every objective. When possible, a small number of experimentally manufactured designs should then be tested to determine whether the numerical ranking survives manufacturing variation and contact-resistance uncertainty. Figure 1 illustrates a representative surrogate-assisted optimization result, in which changes in the cooling-channel geometry alter both the cell-temperature distribution and the pressure field within the coolant passage [40].

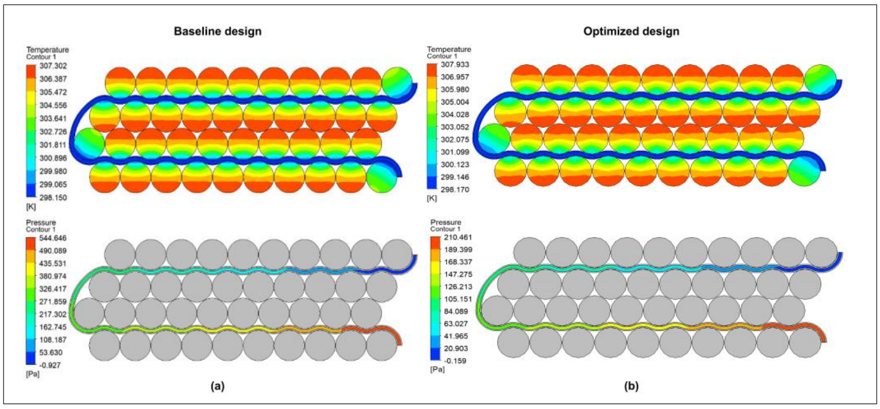

Fig 1: Temperature and pressure distributions of the battery module obtained with (a) the baseline cooling design and (b) the optimized cooling design. Reproduced from Ref. [40]

3.4. Topology and bio-inspired optimization

Bio-inspired optimization begins with a recognizable pattern such as a fishbone, honeycomb, leaf vein, or branching network. The pattern provides a physically meaningful starting point and can improve flow distribution with fewer design variables than free topology optimization [30, 32, 33]. Its weakness is that the performance may depend strongly on a few manually selected ratios or branch locations. The design is inspired by nature, but it is not automatically optimal.

Table 2: Comparison of structural optimization methods.

Method	Best use	Strength and caution	Method
Parametric/DOE	Few variables and clear physics	Interpretable, but limited global search	Parametric/DOE
Metaheuristic	Nonlinear multi-objective design	Flexible, but requires many model evaluations	Metaheuristic
Surrogate-assisted	Expensive CFD optimization	Efficient, but vulnerable to model bias and extrapolation	Surrogate-assisted
Bio-inspired	Structured branching concepts	Good flow intuition, but pattern-dependent	Bio-inspired
Topology optimization	Large geometric freedom	Unconventional layouts, but difficult reconstruction and manufacture	Topology optimization

Topology optimization searches a much larger space by redistributing solid and fluid regions. It can reveal unconventional flow paths that would not emerge from a fixed channel template [34, 35,44]. This is valuable when the heat-source map is non-uniform or when the plate has strong packaging constraints. However, the raw topology often contains narrow passages, disconnected regions, or curved features that are difficult to manufacture. Filtering, minimum feature size, pressure-drop regularization, and geometry reconstruction are therefore essential.
Topology optimization also raises a modeling question. Many methods optimize a steady or homogenized representation rather than the final turbulent or conjugate heat-transfer model. The topology should be reconstructed and verified using the same high-fidelity physics used for the baseline comparison. Without this step, the apparent gain may result from differences between the optimization model and the validation model rather than from the geometry itself.

4. Comparative Synthesis, Research Gaps, and Future Directions

4.1. What can be concluded from the reviewed methods?

No single structural family is superior under all conditions. Parallel channels are favorable when pumping power is tightly limited, but they require careful manifold balancing. Serpentine channels offer robust coverage and simple sealing, but long paths increase pressure drop and coolant warming. Mini-channels provide high heat-transfer area, yet their performance is sensitive to manufacturing tolerance. Jackets and cellular structures are effective for cylindrical cells, while topology and bionic structures are most useful when conventional templates cannot satisfy the heat-source distribution.
The optimization method should match the maturity of the design. A new concept should first be explored using physical reasoning and parametric screening. Surrogate-assisted multi-objective optimization becomes appropriate after the main variables and constraints are defined. Topology optimization should be reserved for problems in which the expected benefit justifies the additional reconstruction, manufacturing, and validation effort. Using a sophisticated optimizer before the physical model is credible only produces a precise answer to an uncertain problem.
The reviewed studies also show that small thermal gains can still be meaningful when they improve temperature uniformity, remove a local hot spot, or reduce auxiliary power without increasing mass. Conversely, a visually large reduction in maximum temperature may have limited system value if it requires excessive flow, a heavy plate, or a narrow operating range. Results should therefore be interpreted in terms of the full thermal-hydraulic and pack-level trade-off.

4.2. Validation, uncertainty, and reproducibility

A recurring weakness is that the cooling model is often validated only against cell temperature while the pressure field, flow distribution, or complete cold plate is not verified. Structural optimization directly modifies the flow path, so temperature-only validation is incomplete. Future studies should report temperature at several locations, inlet and outlet pressure, flow rate, and energy balance. Infrared imaging can supplement embedded sensors but should not replace internal temperature measurements.
Uncertainty should be included explicitly. Cell heat generation, contact resistance, coolant properties, pump performance, and manufacturing dimensions vary in practice. A design that is optimal for nominal values may be fragile. Robust optimization can use multiple ambient temperatures, discharge rates, coolant inlet conditions, and manufacturing perturbations. The objective is then not only low temperature but also low performance variability.
Reproducibility requires complete reporting of geometry, mesh, boundary conditions, material properties, optimization settings, and surrogate-validation data. Studies using NSGA-II or other evolutionary algorithms should report population size, generations, constraint handling, convergence assessment, and the rule used to select the final Pareto design. Without these details, comparisons among algorithms are difficult.

4.3. From component optimization to system co-design

Most studies optimize the cold plate at a fixed coolant condition. A vehicle thermal-management system does not operate this way. Pump speed, chiller capacity, radiator performance, ambient temperature, driving cycle, fast charging, and cabin demand change the available cooling conditions. A geometry optimized at a single inlet temperature and flow rate may not minimize energy consumption over a driving cycle.
The next step is co-design of structure and operating strategy. Structural variables can be optimized together with flow scheduling, inlet-temperature control, or mode switching. The objectives should include battery temperature, temperature uniformity, pumping energy, compressor energy, mass, and durability.
Pack integration also requires attention to electrical isolation, crash protection, serviceability, leakage detection, and thermal-runaway propagation. A cold plate is not an isolated heat exchanger. Its geometry affects module stiffness, assembly tolerance, cell support, and the routing of electrical and coolant connections. Multi-physics co-design should therefore include thermal, hydraulic, mechanical, and packaging constraints.

4.4. Recommended research framework

A practical research framework can be summarized in seven steps. First, define the battery chemistry, cell format, heat-generation model, duty cycle, ambient range, and safety limits. Second, select a manufacturable cooling architecture and a limited set of variables with clear physical meaning. Third, validate the baseline thermal-hydraulic model. Fourth, generate design data using space-filling or adaptive sampling. Fifth, train the surrogate and quantify uncertainty. Sixth, perform constrained multi-objective optimization and retain a Pareto set rather than a single numerical optimum. Seventh, revalidate selected designs using high-fidelity simulation and experiment, followed by a pack- and vehicle-level benefit assessment.
For publication-quality evidence, the final design should be compared with the baseline under identical heat generation, inlet conditions, mesh strategy, and contact assumptions. The paper should report not only percentage improvement but also absolute changes in temperature, temperature difference, pressure drop, pumping power, mass, and key dimensions. A limitations paragraph should state which operating conditions and uncertainties were not tested.
This framework preserves the strengths of the recent optimization literature while addressing its main weaknesses. It uses physical screening before data-driven search, treats

uncertainty as part of the design problem, and requires manufacturability and system value to be assessed before claiming superiority.

5. Conclusions

Structural optimization has become an important part of liquid-cooled battery thermal management because channel geometry affects temperature distribution, coolant flow, pressure loss, and the practical integration of the cooling plate. The reviewed studies indicate that no single channel configuration or optimization method performs best under all operating conditions. Parametric analysis is still useful for identifying influential design variables, while multi-objective algorithms are more suitable when thermal performance must be balanced against hydraulic and manufacturing constraints. Surrogate models can substantially reduce the computational cost of CFD-based optimization, but their predictions need to be checked using the original numerical model and, where possible, experimental data.

Bio-inspired channels and topology optimization provide greater geometric freedom, although their practical benefits depend on minimum feature size, sealing, manufacturing feasibility, and flow-distribution control. Future studies should evaluate optimized structures under several coolant conditions, ambient temperatures, discharge rates, and charging regimes instead of relying on a single operating point. Greater attention is also needed to the combined design of cooling geometry and operating strategy. This direction would help translate numerical optimization results into cooling systems that are reliable, manufacturable, and suitable for module- and pack-level applications.

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