

Article

Thermal–Hydraulic Optimization of a Metal Foam Manifold Cold Plate for Energy Storage Battery Systems Using CFD and Machine Learning

Xiang Li ¹, Yilan Yin ², Jun Ren ¹, Hanshen Li ^{3,*}  and Benjun Xie ¹

¹ Chengdu Engineering Corporation Limited, Power China, Chengdu 611130, China; 2013027@chidi.com.cn (X.L.); p2022260@chidi.com.cn (J.R.); p2024132@chidi.com.cn (B.X.)

² College of Liberal Arts and Comprehensive Sciences, Huaihua Normal College, Huaihua 418000, China; duoduoalive@hhtc.edu.cn

³ China Electric Power Planning & Engineering Institute, Beijing 100120, China

* Correspondence: lhs@ncepu.edu.cn

Abstract

This work presents a new Battery Thermal Management System (BTMS) concept utilizing a metal foam manifold cold plate (MFMCP), developed specifically to meet the rising thermal dissipation needs of lithium-ion batteries. By coupling a manifold flow design and high-conductivity metal foams (characterized via SEM), the system significantly enhanced heat transfer and temperature uniformity. A Local Thermal Equilibrium (LTE) model evaluated thermal–hydraulic performance across varying Reynolds numbers (40–200), foam structures (PPI and porosity), and Al₂O₃ nanofluid concentrations. Results indicated that an optimal foam structure (95 PPI, porosity of 0.905) yielded a significant surface temperature reduction of 15 K. Although the Al₂O₃ nanofluid provided an additional cooling effect of 0.3 K, its pressure penalty lowered the performance evaluation criterion (PEC); the highest initial PEC of 2.57 was established when employing the pure base fluid without any functional additives. A Multi-Layer Perceptron (MLP) model was developed to expedite design validation, achieving high predictive accuracy as evidenced by an R² of 0.983 and an MRE of 1.8%. Subsequent optimization via a genetic algorithm (GA) further increased the maximum PEC by 12% to 2.88. Equal pumping power system simulations indicated that the MFMCP design achieved a peak cell temperature of 304.35 K, outperforming traditional designs which peaked at 308.33 K. Furthermore, transient tests at 1C to 2C discharge rates confirmed consistent cooling improvements, demonstrating the MFMCP's promising potential for dynamic operational conditions.

Keywords: cold plate; MLP; Al₂O₃ nanofluid; battery thermal management; metal foam



Academic Editor: King Jet Tseng

Received: 9 June 2026

Revised: 17 July 2026

Accepted: 20 July 2026

Published: 23 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The rapid development of renewable energy generation projects, such as photovoltaics and wind power, has rendered the intermittency and spatial dispersion of clean electricity increasingly prominent challenges in power system operation and planning [1,2]. Grid-scale energy storage is therefore widely regarded as a key enabling technology to enhance supply–demand balance, improve dispatch flexibility, and maintain grid stability under high renewable penetration [3]. Within the diverse landscape of energy storage technologies, the preeminent position has been secured by lithium-ion battery (LIB)-based systems, which have seen widespread adoption across various sectors. This prominence stems

from their exceptional combination of high energy density, prolonged cycle life, and rapid dynamic response capabilities [4]. Nevertheless, large-format LIB packs deployed in grid-scale energy storage facilities are typically configured with ultra-high cell packing densities and constrained heat dissipation surfaces. This structural design inherently creates thermal bottlenecks, which can trigger severe heat accumulation and pronounced spatial temperature gradients during high-rate charge–discharge cycles or prolonged frequent cycling operations [5,6]. Elevated temperature and large thermal gradients not only accelerate performance degradation and aging, but also increase safety risks associated with thermal runaway propagation, thereby threatening the reliability of the entire energy storage system [7]. Consequently, an advanced battery thermal management system (BTMS) stands as a critical prerequisite for upholding the safe and reliable operation of large-scale LIB energy storage installations [8,9]. In this context, liquid-cooled cold plates have attracted considerable attention because they can provide high heat-removal capability, compact integration, and effective temperature regulation [10,11]. Nevertheless, as the critical component in liquid-cooled BTMS, cold-plate design remains constrained by a fundamental engineering paradox. Improving heat transfer efficiency and temperature uniformity usually increases flow resistance, forcing designers to accept higher pumping-power consumption. This fundamental performance dilemma persists as a critical bottleneck hindering further optimization of liquid-cooled BTMS overall performance [12,13].

To address the aforementioned challenges, extensive efforts have been devoted to enhancing and optimizing cold-plate designs [14,15]. One mainstream approach is conventional parametric (geometric) optimization, where key design variables—such as channel aspect ratio, rib thickness, inlet/outlet placement, header (manifold) dimensions, and flow-path arrangement—are systematically tuned to improve flow distribution and suppress hotspot temperatures. For instance, Zhan et al. [16] carried out an exhaustive investigation focusing on the relationship between inlet–outlet arrangement and the thermal characteristics of cold plates, as well as their overall hydraulic performance. Additionally, the study delved into the effects of critical geometric variables, including channel depth and mass flow rate, to identify optimal design parameters. Their findings revealed that the optimal inlet–outlet layout is highly dependent on specific performance metrics (e.g., maximum temperature, temperature uniformity, or pressure drop), highlighting the inherent trade-offs in cold-plate design that are dictated by layout choices. Keyinci et al. [17] proposed an innovative curved multi-branch liquid-cooled plate with a multi-inlet layout. They systematically compared the thermal–hydraulic performance of different channel configurations using computational fluid dynamics (CFD) simulations. The multi-inlet design significantly improved temperature uniformity and reduced maximum temperature ($T_{\max}$), whereas increasing channel number/complexity tended to raise pressure drop, highlighting the thermal–hydraulic trade-off. On the other hand, topology optimization (TO) has developed into an advanced design approach that intelligently reconstructs channel networks within predefined volume and constraint conditions. It allows for more balanced compromises between enhanced heat transfer efficiency and reduced pressure-drop costs. Mo et al. [18] leveraged TO to develop an optimized liquid cold plate tailored for BTMS, and subsequently conducted a comparative analysis against a traditional straight-channel cold plate. The findings demonstrated that the flow network derived from TO is capable of concurrently reducing both the peak temperature and flow resistance. Furthermore, they performed an exhaustive examination of the effects that different coolant flow rates and inlet temperatures exert on the optimized design’s performance. Chen et al. [19] adopted a two-step approach to create topology-optimized cold plates: initially acquiring 2D channel topologies via TO, then rebuilding corresponding 3D models to perform numerical performance evaluations. Their analyses showed that topology-generated channel networks

outperform traditional layouts (e.g., serpentine/straight) in overall thermal-hydraulic performance, and highlighted the sensitivity of performance to inlet/outlet placement. Ji et al. [20] introduced TO for pouch-battery cold plates while explicitly considering heat-distribution characteristics, and formulated multi-objective problems to maximize heat transfer while minimizing flow resistance. The resulting topology designs (under different inlet-position settings) improved temperature regulation and delivered a better thermal-hydraulic trade-off compared with baseline configurations.

In addition, to overcome the fundamental limitations associated with exclusive geometric optimization—specifically the inevitable trade-off between improving heat transfer capabilities and managing pressure drop penalties—numerous studies have begun implementing advanced heat transfer enhancement methods. These include the introduction of porous metal foam materials within flow channels, which can be configured as full-volume fillings or strategically embedded structural components. Such porous inserts can promote fluid mixing through flow disturbance and provide higher effective thermal conductivity due to their large specific surface area. Ki et al. [21] developed an energy-efficient liquid cooling system that integrates multiscale manifold distributors with a porous metal layer. This innovative design not only optimizes coolant distribution across the target surface but also effectively minimizes heat spreading resistance, thereby enhancing overall thermal management performance. Results demonstrated that, in comparison with a straight-channel module operating at the same flow rate, the proposed design enhanced temperature uniformity by approximately 12.9% and lowered the maximum cell temperature by around 7.4%. It is worth noting that at a flow rate as low as 3 L per minute, the device recorded a $T_{\max}$ of roughly 43.3 °C, and its temperature fluctuation was limited to less than 2 K. Keyhani-Asl et al. [22] developed a hybrid BTMS integrating cold plates with liquid-cooled channels enhanced by copper-foam layers, and optimized the foam-layer thickness to balance heat transfer and pressure loss. Their results showed that an optimized 4 mm foam layer reduced the maximum surface temperature by 9 K while keeping temperature non-uniformity below 1 K under 5C discharge, with minimal pressure-drop penalty and improved energy density by reducing required cold plates. Rabiei et al. [23] put forward a unique Hybrid Liquid Cold Plate design to improve the operational efficiency of BTMS. To optimize cooling performance under different ambient conditions, the researchers designed several cold plate structures, including wavy microchannels, straight microchannels, and metal foam-embedded microchannels, and analyzed their performance under various coolant flow rates (2.5–17 kg/s) and ambient temperatures. Test results revealed that the wavy microchannel design effectively suppressed temperature spikes, achieving a 4–6 °C reduction in maximum temperature when compared to conventional straight microchannels, with improved thermal performance, especially at lower coolant flow rates. Despite these promising thermal improvements, metal-foam-enhanced cold plates still face an inherent trade-off between heat-transfer enhancement and hydraulic performance, because the porous structure may introduce additional viscous and inertial resistance, increase pressure drop, and raise pumping-power requirements. Moreover, most existing studies have focused on conventional straight, wavy, or locally enhanced channels, while the integration of porous metal foam into manifold-based overflow structures remains insufficiently explored.

Furthermore, surrogate-assisted machine-learning optimization has been increasingly adopted to efficiently explore high-dimensional design spaces, striking a more favorable balance between heat-transfer enhancement and flow resistance reduction (pressure-drop/pumping-power) penalties [24–26]. Zheng et al. [27] engineered a deep learning-enabled framework to map cold plate structural attributes to thermal-hydraulic responses, before pairing the trained model with the NSGA-II algorithm for multi-objective opti-

mization; their optimized bionic plate simultaneously reduced the battery temperature difference and pressure drop compared with a conventional design. Ebbs-Picken et al. [28] proposed a generalized cold-plate design optimization pipeline. Using a hierarchical deep encoder–decoder neural network as a surrogate, it predicts full pressure, velocity, and temperature fields to enable NSGA-II-driven evolutionary optimization, with manufacturability constraints integrated into the process; the optimized plates achieved concurrent reductions in maximum temperature, temperature non-uniformity, and pressure loss, with substantially lower computational cost than direct transient CFD-based optimization.

Although manifold cold plates, porous metal foams, nanofluids, and machine-learning-assisted optimization have each demonstrated considerable potential for improving battery thermal management, these enhancement strategies have largely been investigated independently. Existing manifold cold plate studies mainly focus on flow redistribution through channel geometry optimization, whereas porous metal foam studies primarily investigate local heat-transfer enhancement in conventional channels. Similarly, nanofluids have generally been employed to improve coolant thermophysical properties without systematically considering their coupled interaction with manifold structures. Moreover, machine-learning approaches have mainly been applied to temperature prediction or geometric optimization rather than to the coupled optimization of manifold flow distribution, porous morphology, and coolant properties. Therefore, the combined thermal–hydraulic behavior of a nanofluid-cooled, metal-foam-filled manifold cold plate has not yet been systematically investigated for large-capacity battery energy storage systems.

To address this gap, the present study develops an integrated thermal–hydraulic design and optimization framework that combines a manifold cold plate, metal-foam-filled overflow channels, Al_2O_3 –water nanofluid, CFD simulations, and machine-learning-assisted optimization. The manifold architecture is employed to improve coolant distribution and repeatedly regenerate the thermal boundary layer, while the metal foam increases the effective heat-transfer area, enhances solid–fluid thermal transport, and promotes local fluid mixing. The nanofluid further modifies the coolant thermal conductivity, heat capacity, viscosity, and density, resulting in coupled effects on both heat transfer and pressure loss. These interactions are first evaluated at the periodic overflow-unit level over different Reynolds numbers, foam morphologies, and nanoparticle concentrations. An MLP surrogate model is subsequently trained using the CFD dataset and coupled with a genetic algorithm to efficiently identify the parameter combination that maximizes the performance evaluation criterion. Finally, the optimized configuration is assessed at the full battery-pack level under equal pumping power and transient discharge conditions.

2. Methodology

2.1. Geometric Model

For this study, a representative lithium-ion battery pack for energy storage applications was selected, consisting of 52 prismatic cells arranged in a 4×13 configuration. The overall dimensions of the battery pack are 978 mm $\times$ 704 mm $\times$ 207 mm, and each cell is a 280 Ah LiFePO_4 battery with dimensions of 173 mm $\times$ 71 mm $\times$ 207 mm. The equivalent density and specific heat capacity of the battery pack are 2238.9 kg/m³ and 1190 J/(kg·K), respectively. Owing to the layered internal structure of the prismatic cells, anisotropic thermal conductivity was adopted, with a value of 20.2327 W/(m·K) in the x- and z-directions and 6.0835 W/(m·K) in the y-direction. The manifold channel has a height of 2 mm and a width of 2 mm, while the overflow channel has a height of 6 mm and a width of 4 mm. These dimensional parameters play a key role in determining the cooling efficiency and thermal performance of the system. As depicted in Figure 1, battery racks for energy storage systems are usually assembled from multiple modules, each combining

lithium-ion batteries with an integrated cold plate. The module utilized in this research consists of 52 series-linked LFP batteries, with a cold plate mounted at the base of the battery stack. This advanced cold plate design integrates a dual-manifold system, where cooling fluid enters through the primary inlet manifold, flows through precision-engineered inlet channels, and is then channeled into overflow channels that prevent flow stagnation and enhance heat transfer efficiency across the entire plate surface. As the heat exchange process proceeds, the coolant reverses its flow path, passing through the channels linked to the outlet manifold and converging into the manifold structure before exiting the cold plate assembly. The manifold-channel cold plate design transforms the coolant flow from a conventional single-inlet, single-outlet configuration into a more complex multi-inlet, multi-outlet intermittent flow pattern. This design maximizes the entrance effect, improving heat transfer efficiency. To further enhance the cold plate's heat transfer capabilities, porous metal foam was incorporated into the overflow channels in this study. Four types of metal foams, each with different PPI (pores per inch), were selected. The ligament thickness (d_f) and pore diameter (d_p) of these metal foams were measured using scanning electron microscopy (SEM, Phenom ProX, Thermo Fisher Scientific, Waltham, MA, USA), providing detailed insights into their microstructure.

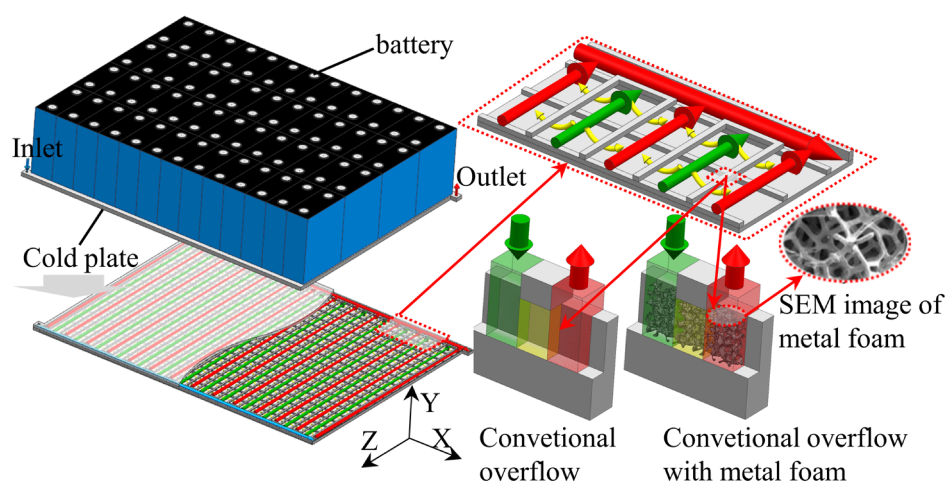


Figure 1. Conceptual layout of the battery pack cooling system using a metal-foam-filled manifold cold plate.

In this study, four different metal foam configurations are considered, each characterized by varying PPI (pores per inch), porosity (ϵ), pore diameter (d_p), and ligament thickness (d_f). Four distinct cases of porous structures are analyzed, with key morphological parameters summarized as follows:

Case 1: This configuration has a PPI of 35, a porosity level of 0.933, a pore diameter ranging from 0.68 to 0.72 mm, and a ligament thickness between 0.30 and 0.34 mm.

Case 2: With a PPI of 40, this case shows a marginally higher porosity of 0.944 compared to Case 1, paired with an expanded pore diameter of 0.78–0.82 mm and a reduced ligament thickness of 0.18–0.22 mm.

Case 3: Featuring a PPI of 60, this structure shares the same 0.933 porosity as Case 1, but has a narrower pore diameter of 0.41–0.45 mm and a ligament thickness of 0.19–0.23 mm.

Case 4: Representing the extreme end of the parameter spectrum, this case has the highest PPI (95) alongside the lowest porosity (0.905), smallest pore diameter (0.25–0.29 mm), and thinnest ligament thickness (0.14–0.18 mm).

These distinct metal foam configurations are specifically chosen to investigate their effects on thermal and flow performance within the battery pack cooling system. Given that pore structures directly dictate heat transfer efficiency and flow resistance, variations

in these structures are anticipated to exert a notable influence on the overall performance of the cooling system.

2.2. Geometry and Simulation Cases

Al₂O₃ nanofluid is formulated by dispersing aluminum oxide nanoparticles in deionized water, with the resulting suspension treated as a homogeneous single-phase medium within the present numerical framework. Three nanoparticle volume fractions, $\phi = 1\%$, 3% , and 5% , are examined. The correlations and procedures adopted to determine the thermophysical properties of the nanoparticle-base-fluid mixture are summarized in Table 1.

Table 1. Water-based Al₂O₃ nanofluid thermophysical properties prediction model.

Parameter	Water	Al ₂ O ₃	Water-Based Al ₂ O ₃ Nanofluid	Reference
ρ (kg/m ³)	$\rho_{bf} = 998.2$	$\rho_{np} = 3970$	$\rho_{nf} = (1 - \phi)\rho_{bf} + \phi\rho_{np}$	G. Topcu et al. [29], S. A. Khan et al. [30]
C_p (J/kg · K)	$c_{p,bf} = 4190$	$c_{p,np} = 765$	$c_{p,nf} = (1 - \phi)c_{p,bf} + \phi c_{p,np}$	M. K. Najafabadi et al. [31], B. N. RAO and T. Sreedhar [32]
k (W/m · K)	$k_{bf} = 0.613$	$k_{np} = 40$	$k_{nf} = \frac{k_{np} + 2k_{bf} - 2(k_{bf} - k_{np})\phi}{k_{np} + 2k_{bf} + (k_{bf} - k_{np})\phi} k_{bf}$	M.R. Sohel et al. [33], M. K. Moraveji and R. M. Ardehali [34]
μ (Pa · s)	$\mu_{bf} = 0.001005$	-	$\mu_{nf} = \mu_{bf}(123\phi^2 + 7.3\phi + 1)$	A. M. Ali et al. [35]

2.3. CFD Model Construction Methodology

2.3.1. Governing Equation

Since the Reynolds number in the clear-fluid (non-metal-foam) region is below 200, the flow is modeled as laminar. In the porous zone, the superficial/average velocity varies from 0.01 to 0.07 m/s, which falls within the applicability range of the Brinkman–Darcy–Forchheimer formulation as reported in the literature [36,37]. When the coolant temperature variation is as small as 9 K, the corresponding changes in its thermophysical properties listed in Table 1 can be neglected [38]. Under these assumptions, the governing equations can be written in the simplified form:

Continuity equation [39]:

$$\frac{\partial \rho}{\partial t} + \frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} + \frac{\partial u}{\partial z} = 0 \quad (1)$$

Momentum equation of fluid in the non-metal foam region [40]:

$$\rho_f \left(\frac{\partial u}{\partial t} + (u \times \nabla)u \right) = -\nabla p + \mu \nabla^2 u \quad (2)$$

- u represents the velocity.
- ρ_f represents the density.
- p represents the pressure.
- μ represents the viscosity.

The Brinkman–Darcy–Forchheimer model for the porous region [41]:

$$\frac{\rho}{\varepsilon^2} (u \times \nabla)u = -\nabla p + u \nabla^2 u - \frac{\mu}{K_F} u - \frac{\rho F}{\sqrt{K_F}} |u|u \quad (3)$$

- K_F represents the Forchheimer permeability.
- F represents the Forchheimer coefficient.
- ε represents the porosity of the metal foam.
- K_F and F are computed via:

$$K_F = 0.00073(1 - \varepsilon)^{-0.224}(d_f/d_p)^{-1.11}d_p^2 \quad (4)$$

$$F = 0.00212(1 - \varepsilon)^{-0.132}(d_f/d_p)^{-1.63} \quad (5)$$

The strut diameter (d_f) and pore diameter (d_p) were extracted from SEM characterization. Using Equations (4) and (5), the resulting permeability K_F and inertial factor F for metal foams at various PPI levels are computed and tabulated as follows: Case 1 with K_F of 1.56, F of 0.01085; Case 2 with K_F of 4.15, F of 0.02971; Case 3 with K_F of 0.548, F of 0.00974; Case 4 with K_F of 0.161, F of 0.00679.

In porous-media heat transfer analyses, the Local Thermal Equilibrium (LTE) model operates on the premise that the solid and fluid phases within a control volume maintain thermal equilibrium, meaning both phases share a uniform temperature field. Although heat is exchanged between the solid skeleton and the fluid, the resulting temperature deviation between them is considered very small [42,43]. Accordingly, the governing energy equation for the LTE model can be expressed as:

LTE model [44]:

$$\rho_f c_{p,f} \left(\frac{\partial T_f}{\partial t} + u \times \nabla T_f \right) = \nabla \times (k_{eff} \nabla T_f) + S \quad (6)$$

- $c_{p,f}$ represents the specific heat capacity of the fluid.
- T_f represents the temperature of the fluid.
- k_{eff} represents the effective thermal conductivity.
- S represents the heat source.

Solid domain:

$$\rho_s c_{p,s} \frac{\partial T_s}{\partial t} = \nabla \times (k_s \nabla T_s) + S \quad (7)$$

- $c_{p,s}$ represents the specific heat capacity of the solid.
- T_s represents the temperature of the solid.
- k_s represents the thermal conductivity of the solid.

To enable a rigorous comparative assessment of the overflow unit across different operating conditions, a suite of thermal and hydraulic performance indicators is defined. These include Reynolds number (for flow regime characterization), hydraulic diameter (for channel geometry), convective heat transfer coefficient and Nusselt number (for heat transfer performance), friction factor (for flow resistance), and PEC (for comprehensive performance evaluation) [45,46]. The calculation methods for each parameter are provided as follows:

Reynolds number:

$$Re = \frac{\rho u D}{\mu} \quad (8)$$

where D is defined as the hydraulic diameter of the overflow channel and can be calculated by:

$$D = \frac{2h_m \times w_m}{h_m + w_m} \quad (9)$$

where h_m represents the height of the manifold channel, and w_m represents its width.

Local heat transfer coefficient for the overflow channel:

$$h = \frac{q}{T_{base,ave} - T_m} \quad (10)$$

In the present study, q is the heat flux on the heating surface, $T_{base,ave}$ is the average heating-surface temperature, and T_m is the mean fluid temperature, taken as the average of the inlet and outlet temperatures:

$$T_m = \frac{T_{in} + T_{out}}{2} \quad (11)$$

where T_{in} and T_{out} correspond to the temperatures of the fluid at the inlet and outlet, respectively.

The average Nusselt number is calculated as follows:

$$Nu = \frac{h \times D}{k} \quad (12)$$

Friction factor:

$$f = \frac{\Delta p \times D}{1/2 \times (\rho u^2 L)} \quad (13)$$

where Δp represents the pressure drop at the inlet and outlet, and L represents the length of the overflow channel.

For heat exchanger assessment, the Nusselt number is commonly used to quantify heat-transfer performance, whereas the friction factor (f) reflects flow resistance. To concurrently address both the enhancement of thermal efficiency and the accompanying hydraulic penalty, the performance evaluation criterion (PEC) is adopted as a unified indicator for design assessment. The PEC is defined in terms of Nu and f as:

$$PEC = \frac{Nu/Nu_0}{(f/f_0)^{1/3}} \quad (14)$$

The pumping power required to circulate the coolant through the cold plate is calculated as:

$$P_p = \Delta p \times Q_{inlet} \quad (15)$$

- P_p represents the pumping power,
- Δp represents the pressure drop of the inlet and outlet.
- Q_{inlet} represents the volumetric flow rate at the inlet.

2.3.2. Battery Heat Generation Model

In Equation (7), denotes the battery heat generation rate, which is calculated as:

$$S = \frac{Q_b}{V_b} \quad (16)$$

where V_b represents the volume of the battery, and Q_b corresponds to the heat generation during the charge–discharge process, expressed as:

$$Q_b = I^2 R - IT \frac{dV_{oc}}{dT} \quad (17)$$

where I , R_i , T and V_{oc} are the current, internal resistance, battery temperature, and open-circuit voltage, respectively. The derivation and implementation steps are provided in the corresponding reference [47].

The heat generation function of the battery is delineated as follows:

$$Q_b = \begin{cases} 19.5 - 779 \times DOD + 22125.1 \times DOD^2 - 30960 \times DOD^3 + 2469540 \times DOD^4 \\ - 11986800 \times DOD^5 + 35993900 \times DOD^6 - 65200200 \times DOD^7 + \\ 65197800 \times DOD^8 - 27607400 \times DOD^9, & DOD < 0.16 \\ 16 - 39 \times DOD + 55.9612 \times DOD^2 - 60.0829 \times DOD^3, & 0.16 \leq DOD < 0.37 \\ 3.16516 - 163.279 \times DOD + 656 \times DOD^2 + 668.94 \times DOD^3, & 0.37 \leq DOD < 0.5 \\ 46.83774 - 401.20154 \times (1 - DOD) + 2301.55062 \times (1 - DOD)^2 - 7355.81 \times (1 - DOD)^3 \\ + 11143.95 \times (1 - DOD)^4 - 6219.8834 \times (1 - DOD)^5 & DOD \geq 0.5 \end{cases} \quad (18)$$

where DOD , the Depth of Discharge, can be converted to the State of Charge (SOC):

$$SOC = SOC_{initial} - \frac{I \times t}{3600C_{cap}} \quad (19)$$

$$DOD = 1 - SOC \quad (20)$$

Figure 2 illustrates the heat generation rate and output voltage profiles during the 0.5 C discharge process at 25 °C. A distinct peak emerges at the initial discharge stage (when the depth of discharge, DOD , is below 0.005), followed by a continuous decline that persists until DOD reaches approximately 0.5, before a remarkable upward trend occurs in the late phase of the discharge cycle.

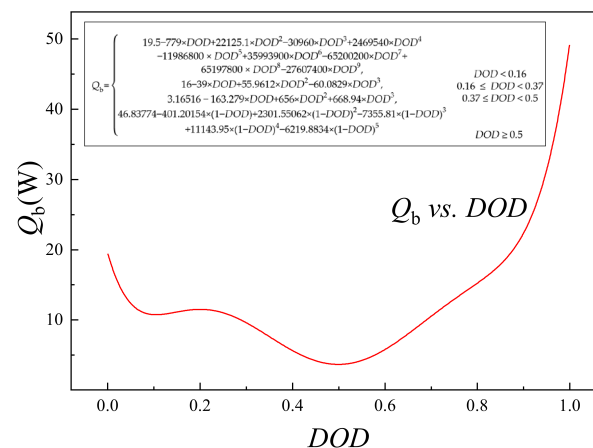


Figure 2. Heat generation rates at various depths of discharge [47].

2.3.3. Calculation Model and Assumptions

Discretization of governing equations was performed using the finite volume method, with ANSYS 2024 R1 Fluent employed for solution. A segregated solver with the SIMPLEC pressure–velocity coupling scheme was employed. Spatial gradients were evaluated through a cell-based least-squares method, with pressure discretized to second-order accuracy. Meanwhile, second-order upwind schemes were utilized for the discretization of momentum and energy equations. To enhance computational efficiency, a two-stage simulation strategy is adopted in this study. In the first stage, the overflow unit is prioritized for simulation to screen the optimal metal foam configuration. Given that this stage prioritizes comparing the thermal performance of distinct metal foam assemblies over capturing dynamic thermal responses, a steady-state simulation was judged to meet the requirements. A uniform heat flux boundary condition was imposed on the interface between battery cells and the hollow cold plate. To ensure the experimental results accurately reflect the effect of metal foam on heat dissipation, heat transfer between the overflow unit and ambient surroundings was intentionally excluded from the analysis, creating a controlled thermal

environment that isolates the variable of interest. Upon identifying the optimal metal foam combination through the first-stage screening, the second stage focuses on simulating the entire battery pack to validate the thermal management performance under more realistic operating conditions. Both steady and transient simulations are conducted in this stage to comprehensively evaluate the thermal behavior of the battery pack. Unlike the first stage, heat exchange between the battery pack and the ambient environment is considered, with a convective heat transfer coefficient set to $5 \text{ W}/(\text{m}^2 \cdot \text{K})$ and a constant ambient temperature of 297 K .

2.3.4. Mesh Independence Check

To verify mesh independence, a mesh sensitivity analysis was conducted, tracking average heating-surface temperature and inlet–outlet pressure difference, as shown in Figure 3. When the total cell count is greater than 0.36 million, these indicators remain essentially unchanged, confirming that further mesh refinement has little effect on the results.

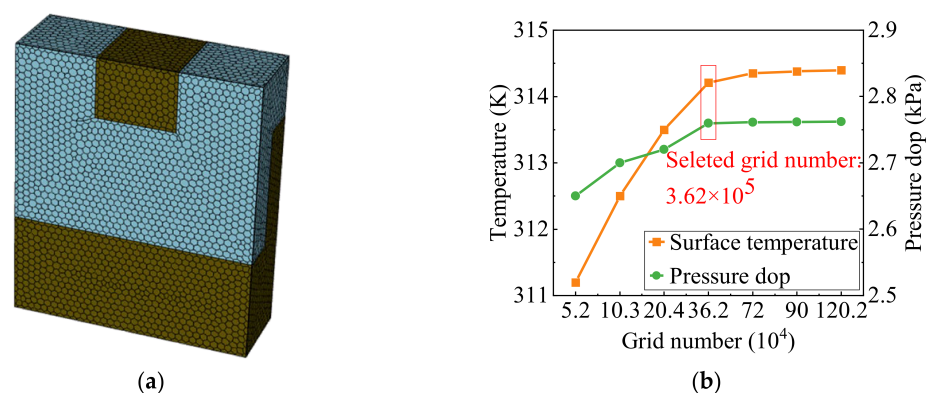


Figure 3. Mesh division and verification of overflow unit: (a) mesh division; (b) mesh independence verification.

2.3.5. Numerical Validation

To further assess the accuracy of the numerical methodology adopted in this study, two components of the computational framework were validated separately. First, the fluid-flow and heat-transfer model for the metal-foam-filled manifold cold plate was validated by reproducing the geometric model, boundary conditions, and operating parameters reported in Reference [21]. As shown in Figure 4, the predicted pressure drop and heating-surface temperature rise under different flow conditions agree well with the corresponding published results, supporting the reliability of the adopted porous-medium flow and conjugate heat-transfer models. Second, the transient battery thermal model was validated using the experimentally measured average surface temperature of a 280 Ah battery under a 0.5C discharge condition reported in Reference [47]. As shown in Figure 5, the simulated and experimental temperature histories exhibit consistent nonlinear increasing trends, and the maximum deviation remains below 5%. This agreement confirms the applicability of the transient battery heat-generation and heat-transfer treatment adopted in the present study.

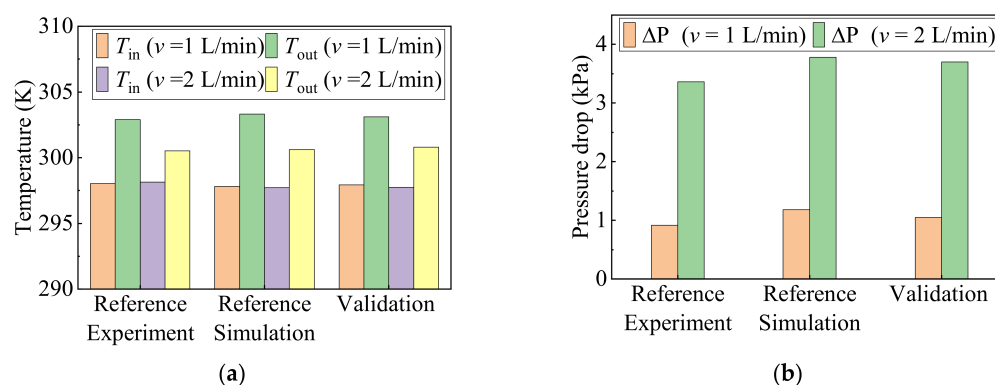


Figure 4. Comparative analysis of simulation, experimental, and literature data under multiple flow conditions: (a) maximum inlet/outlet and average temperatures; (b) pressure drop [21].

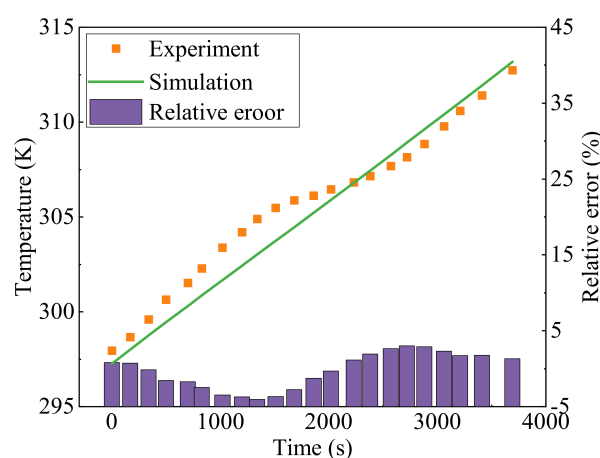


Figure 5. Battery heat generation validation [47].

2.4. Using Machine-Learning Methods

Machine learning (ML), a core branch of artificial intelligence (AI), establishes a paradigm enabling AI systems to autonomously acquire knowledge and enhance their performance through exposure to data. Establishing correlations between numerous variables traditionally demands considerable effort and time, primarily due to the intensive mathematical modeling and analytical work required. The implementation of machine-learning methodologies, however, offers a pathway to substantially expedite and automate this procedure, thereby minimizing the subsequent modeling and analytical burden in practical settings.

Following the training phase, these ML models can be applied to new datasets, enabling researchers to carry out comprehensive analyses in a significantly shorter period. What is more, machine-learning models exhibit greater adaptability and resilience across various practical scenarios, as they are engineered to support a wider range of data formats and operational environments. Leveraging these advantages, a Multi-Layer Perceptron (MLP) architecture was constructed specifically to tackle the challenges identified in this study.

2.4.1. Multi-Layer Perceptron

In predictive modeling, the MLP is a commonly used feedforward artificial neural network. A minimal MLP structure consists of an input layer, one or more hidden layers, and an output layer. In a “fully connected” MLP, every node in one layer is connected by weighted links to all nodes in the subsequent layer. To fulfill the regression prediction objective of this study, an MLP model was developed. The architecture and learning behavior

of an MLP are governed by a set of structural and configurable settings, commonly referred to as hyperparameters (e.g., the number of hidden layers, neurons per layer, learning rate, activation function). Crucially, unlike internal parameters such as weights and biases that are iteratively adjusted through gradient-based backpropagation, hyperparameters are predetermined and remain static during training; they cannot be derived automatically by the model and must be explicitly configured prior to the learning process. Their selection plays a decisive role in shaping both the learning dynamics and the eventual predictive performance of the model. In this work, the Adam optimization algorithm was utilized for training, with a weight-decay coefficient of 10^{-4} to mitigate overfitting. Concurrently, a grid-search approach was implemented to systematically and exhaustively fine-tune these principal hyperparameters across the predefined numerical ranges outlined in Table 2. The procedure ultimately identified the hyperparameter configuration that yielded optimal model performance, manifested as the highest convergence efficiency during training alongside superior generalization capability on the testing set.

Table 2. Optimal hyperparameters.

Hyperparameters	Search Range	Final Value
Number of hidden layers	2, 3, 4, 5, 6	4
Neurons per hidden layer	7, 14, 28	14
Learning rates	0.001, 0.01, 0.1	0.001
Activation functions	Relu, tanh	Relu
Epochs	200, 500, 1000, 2000	1000

Figure 6 depicts the architectural configuration of the MLP implemented in this research. The constructed network employs a five-layer topology, comprising an input layer, three successive hidden layers, and an output layer. Seven neurons populate the input layer, corresponding to the seven distinct input features, whereas the output layer is configured with a single neuron dedicated to predicting the PEC value. Each of the three intermediate hidden layers is uniformly designed with fourteen neurons. Computational execution was performed on an RTX 2080 Ti graphics processing unit (GPU), within a Python 3.7 programming environment. The PyTorch 1.8.1 framework coupled with CUDA 11.0 was leveraged to accelerate model training and inference processes.

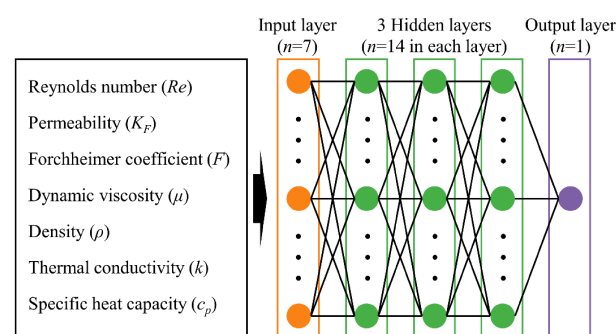


Figure 6. The architectural configuration of the MLP.

2.4.2. Data Gathering and Preprocessing Workflow

The dataset plays a critical role in training machine-learning models. To enhance the model's performance and ensure the integrity of the data, various preprocessing steps were implemented prior to training. These steps included data cleaning and normalization. A dataset comprising 150 samples was obtained from computational simulations. Following standard practice in machine learning, the dataset was segmented, with 80% designated for the training phase and the remaining 20% for the testing phase. As outlined in Table 3, the

selected features include both input and output parameters. Among these, inlet velocity, permeability, and the Forchheimer coefficient are directly correlated with the PPI and porosity of the medium. In parallel, the concentration of the nanofluid serves as the governing variable for its thermophysical properties, including density, dynamic viscosity, specific heat capacity, and thermal conductivity. These input parameters significantly impact both Nusselt number (Nu) and the friction factor (f). The output variable predicted by the model is the PEC, which incorporates the effects of both Nu and f .

The dataset for this analysis originated from Fluent simulation outputs, where each individual case was confirmed to have reached a converged state. Subsequent to data acquisition, the first procedural step comprised a quality control check to identify and correct any erroneous, missing, or logically inconsistent entries. To simplify subsequent processing, duplicate entries and redundant data points were removed. Furthermore, to standardize the input features, all numerical values were normalized to a common scale, typically between 0 and 1. A small offset of 0.01 was applied to the permeability and Forchheimer coefficient values to enhance numerical stability and smooth out the input range, as suggested by previous studies [48]. In addition, the output data were rescaled to the 0–1 range using the functions outlined in Table 3.

Table 3. Input parameters with corresponding value ranges and scaling functions for the model.

Parameters	Type	Min Value	Max Value	Functions
K_F	Input	0	1.47×10^{-8}	$x_{rescale,i} = 0.99 \frac{x_i}{x_{max}} + 0.01$
F	Input	0	9.57×10^{-2}	
Re	Input	20	160	$x_{rescale,i} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$
c_p	Input	4009.55	4182	
μ	Input	0.001003	1.677×10^{-3}	
k	Input	0.6	0.69	
ρ	Input	998.2	1142.29	
PEC	Output	0.82	2.57	

2.4.3. Metrics for Evaluating Machine-Learning Model Performance

To evaluate how effectively and accurately machine-learning models perform, performance metrics are essential. Through quantitative analysis, these metrics gauge both the model's capacity for precise forecasting and the extent of its prediction errors. In this study, the performance of the machine-learning models is assessed using the following key metrics: Mean Absolute Error (MAE), Mean Relative Error (MRE), Root Mean Squared Error (RMSE), and R^2 . The definitions of each metric are provided below [48,49]:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (21)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{y_i} \times 100\% \quad (22)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (23)$$

$$R^2 = \frac{\sum_{i=1}^n (\bar{y}_i - y_i)^2}{\sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i \quad (24)$$

where n represents the sample size, y_i represents the actual value, and $\hat{y}_i$ represents the predicted value.

2.5. Optimization Method

In this study, the enhancement of the PEC primarily addresses the fundamental compromise between flow resistance and thermal performance. Since machine-learning approaches have uncovered intricate nonlinear correlations among multiple design variables and the PEC, a genetic algorithm (GA) was utilized in this investigation to determine the most effective configuration of these parameters. The objective of the algorithm is to maximize the PEC, which is essentially equivalent to achieving an optimal balance between flow resistance and thermal dissipation performance. The GA stands out as a highly effective tool for this optimization task, owing to its robust global search prowess and strong compatibility with intricate nonlinear systems. By iteratively searching through potential parameter combinations within the defined design space, the algorithm thoroughly explores possible solutions and ultimately converges to the optimal one. For specific details on the GA methodology and its application in this context, readers are referred to the relevant literature [50].

3. Results and Discussion

3.1. Impact of the Porous Metal Foam on Thermal and Flow Performance

This section utilizes numerical simulations to examine the influence of four different metal foam configurations (Cases 1–4) on the thermal and flow performance within the overflow unit. Furthermore, the traditional MCP design with pure water is labeled as Case 0 for comparison.

To intuitively understand the impact of metal foam on the heat dissipation performance of cooling units, a comparison of the surface temperatures of cooling units under different schemes should be prioritized. Given that the surface temperatures of the cooling units in Cases 1–4 with metal foam added are comparable, Case 2 is selected as a representative for comparison with Case 0, as illustrated in Figure 7.

The overall temperature of Case 2 is significantly lower, with the maximum temperature in the solid domain reduced by 25% (approximately 8 K) compared to Case 0. In Case 0, the surface temperature of the fluid shows almost no variation, whereas in Case 2, the fluid temperature changes remarkably, and distinct thermal boundary characteristics between the fluid and solid domains are observed. This indicates that metal foam substantially enhances the heat transfer intensity of the fluid, resulting in a large temperature difference between the fluid inlet and outlet. Additionally, the temperature distribution in the solid domain of Case 2 is fairly uniform, with almost no temperature difference, demonstrating that metal foam can also improve the uniformity of heat transfer.

The incorporation of metal foam markedly improves flow uniformity by facilitating a more laminar flow regime within the overflow unit. As Cases 1–4 exhibit analogous flow patterns, Figure 8 presents a comparative analysis of velocity vectors between the baseline design (Case 0) and a representative enhanced configuration (Case 2). Figure 8a (Case 0) exhibits distinct velocity stratification, characterized by higher flow velocities at the channel top and significantly reduced speeds near the bottom. In comparison, Figure 8b (Case 2) reveals a substantially different flow field. The metal foam located at the channel base effectively mitigates this stratification. The flow velocity in the bottom region is considerably elevated, suggesting that the porous structure disturbs the fluid flow and enhances momentum exchange. This active mixing promotes a more homogeneous velocity profile across the entire channel cross-section. Consequently, the metal foam serves to optimize the flow dynamics, which directly contributes to superior thermal performance and more effective heat dissipation.

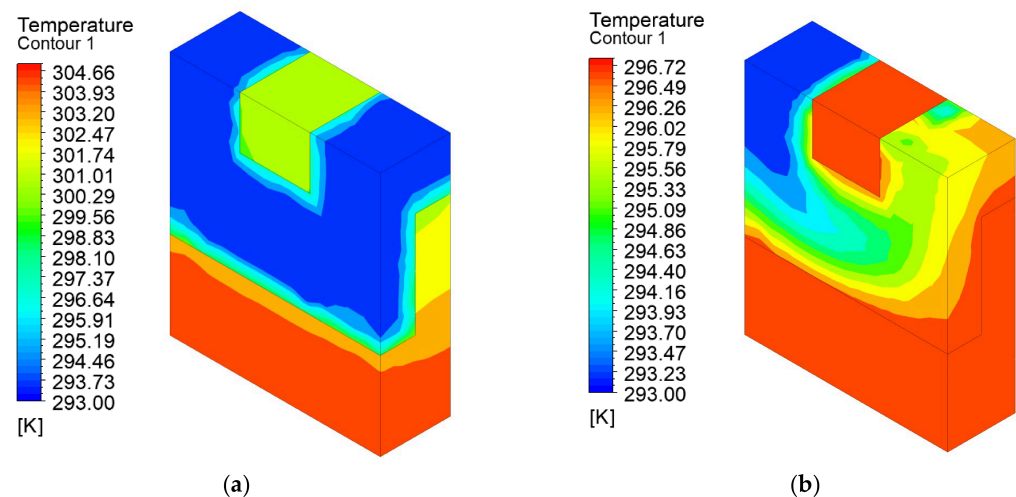


Figure 7. Surface temperature contours for Cases 0 and 2 when $Re = 80$ and $\phi = 0$: (a) Case 0; (b) Case 2.

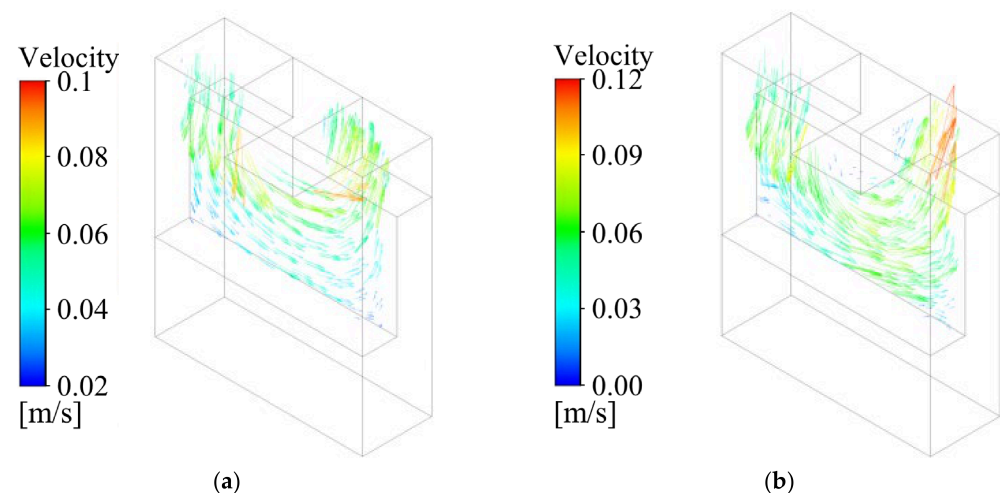


Figure 8. Velocity vector plot for Cases 0 and 2 when $Re = 80$ and $\phi = 0$: (a) Case 0; (b) Case 2.

Comparing the average temperature of the heating surface provides a direct and intuitive measure of how effectively each design removes heat. As shown in Figure 9a, increasing the flow rate (Re) reduces the average heating surface temperature for all configurations, while the four MFMCP cases (Cases 1–4) consistently maintain markedly lower temperatures than the baseline serpentine plate (Case 0). At $Re = 80$, for example, Case 4 yields an average heating surface temperature of 297.3151 K, approximately 11 K lower than that of the conventional serpentine design. This pronounced reduction demonstrates that inserting metal foam into the overflow channels substantially strengthens convective heat transfer, thereby improving the cooling effectiveness of the manifold cold plate. Among the foam-enhanced configurations, Case 4 generally provides the lowest average surface temperature over the entire Re range. Nevertheless, the differences among Cases 1–4 remain small, indicating that these MFMCP variants deliver comparable temperature-control capability. Figure 9b further corroborates this trend by presenting the variation in the Nusselt number (Nu) with flow rate. Overall, the MFMCP designs exhibit significantly higher Nu than Case 0, confirming enhanced heat-transfer performance. Case 4 achieves the largest Nu throughout the studied range, increasing from about 78 at $Re = 40$ to roughly 130 at $Re = 200$. In contrast, Case 2 shows the smallest heat-transfer gain, with Nu rising from approximately 68 at $Re = 40$ to just above 115 at $Re = 200$. The Nu curves of Cases 1 and 3 almost overlap, suggesting similar heat-transfer behavior for these two configurations.

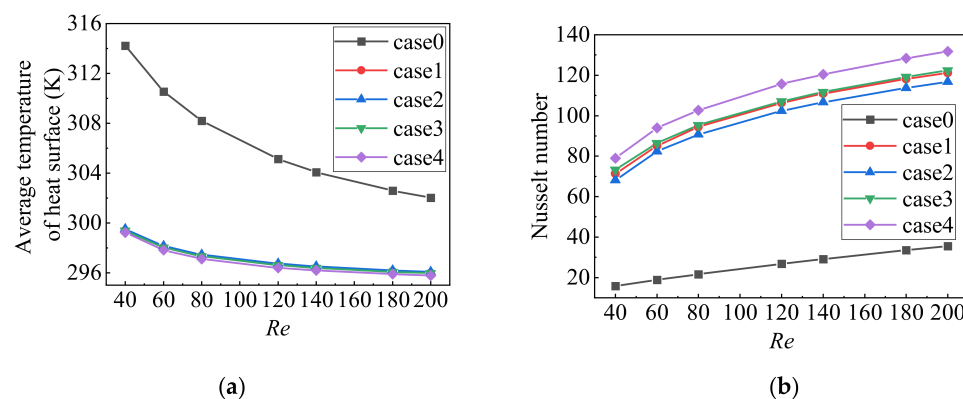


Figure 9. The average temperature of heating surface and Nusselt number change with Reynolds number: (a) average temperature; (b) Nusselt number.

3.2. Impact of the Water-Based Al_2O_3 Nanofluid on Thermal and Flow Performance

To investigate the impact of Al_2O_3 nanofluid on the thermal and flow performance of MFMCP, Figure 10 illustrates the maximum temperature of the heating surface across a range of Reynolds numbers for four distinct concentrations of Al_2O_3 nanoparticles: 0 vol% (pure water), 1 vol%, 3 vol%, and 5 vol%. The findings indicate a consistent trend in which increasing the concentration of nanoparticles is associated with a slight decrease in the maximum temperature, suggesting a measurable improvement in the cooling performance of the MFMCP system. As an example, in Case 1 at $Re = 40$, the maximum temperature of the overflow unit's heat surface decreases relative to pure water (0 vol%) by roughly 0.1 K, 0.15 K, and 0.3 K for nanofluid concentrations of 1, 3, and 5 vol%, respectively. This pattern persists across Cases 2–4, indicating that while nanofluids do improve thermal performance, their impact becomes less pronounced as the Reynolds number rises. This suggests that the contribution of nanoparticles to heat transfer diminishes under conditions of higher flow velocity.

Figure 11 illustrates the correlation between pressure drop and PEC across varying Reynolds numbers for nanofluids with distinct nanoparticle volume fractions ($\phi = 0, 1, 3$ and 5 vol%). As depicted in Figure 11a, a consistent trend emerges: under identical operating conditions, both inlet and outlet pressure drops escalate with increasing nanoparticle concentration across all test cases. While nanofluid incorporation enhances the heat transfer capacity of the MFMCP units, it concurrently elevates flow resistance, necessitating a comprehensive PEC analysis to quantify this trade-off. A comparative visualization of PEC values for the four experimental setups is provided in Figure 11b. Analysis indicates that PEC progressively diminishes with increasing nanofluid concentration. Taking Case 1 at an inlet Reynolds number of 40 as an instance, the PEC reduces from 2.35 under pure base fluid conditions ($\phi = 0$) to 2.25 when the nanoparticle volume fraction reaches 5%. This pattern is consistently replicated in Cases 2, 3, and 4, indicating that despite the heat transfer improvements afforded by nanofluid, these gains are partially offset by the augmented pressure drop. Consequently, the overall enhancement in heat transfer efficiency becomes relatively marginal when weighed against the corresponding increase in flow resistance.

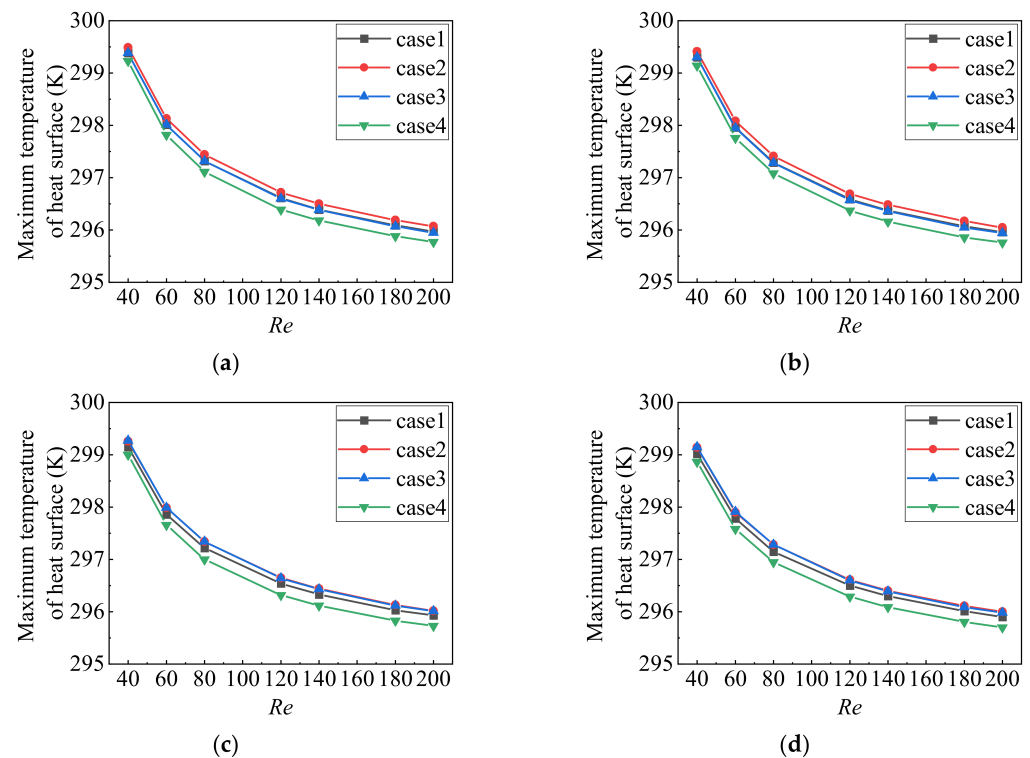


Figure 10. Influence of Reynolds number on the maximum heating surface temperature for different Al_2O_3 nanoparticle volume fractions: (a) $\phi = 0$ vol%; (b) $\phi = 1$ vol%; (c) $\phi = 3$ vol%; (d) $\phi = 5$ vol%.

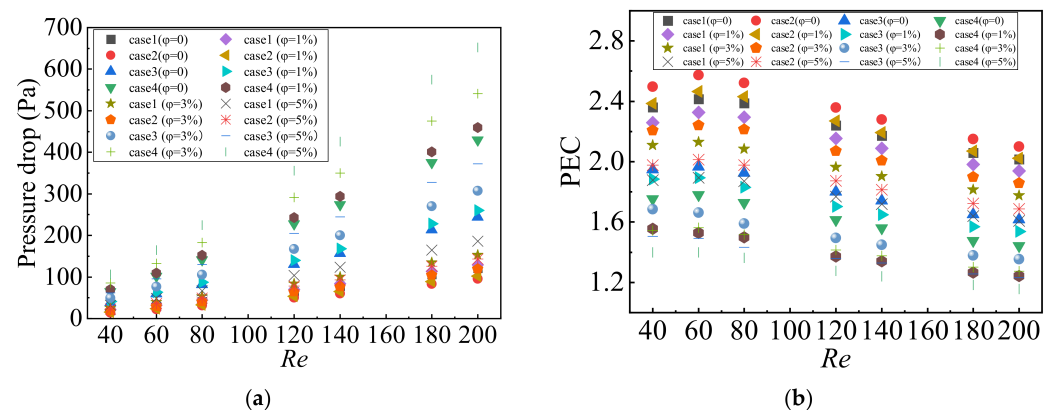


Figure 11. Variations in pressure drop and PEC with Reynolds number at different nanofluid volume fractions: (a) pressure drop; (b) PEC.

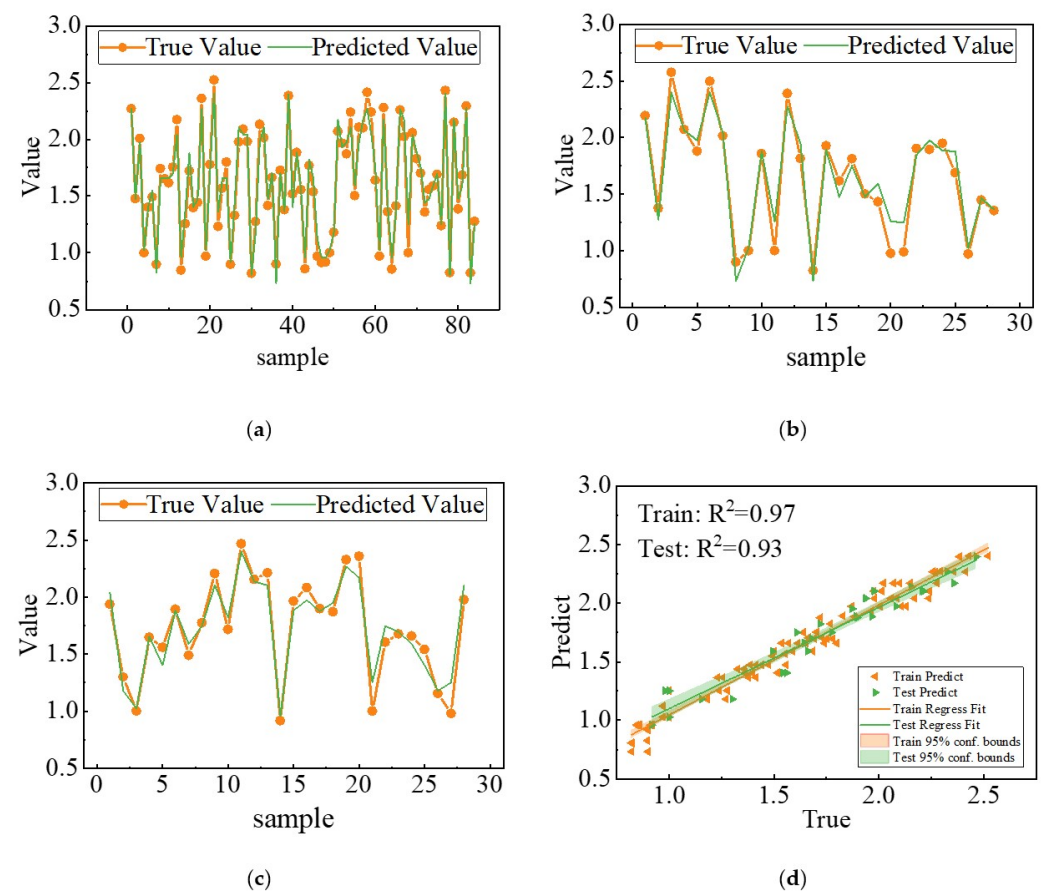
3.3. Analysis and Evaluation of the Developed Machine-Learning Model

In this work, an MLP model was constructed to forecast the PEC, with its predictive performance rigorously assessed using key metrics including R^2 , RMSE, MAE and MRE. To diagnose potential overfitting or underfitting issues, a comparative analysis of R^2 values between the training and testing datasets was conducted. A substantial discrepancy, characterized by a high training R^2 paired with a significantly lower testing R^2 , is indicative of overfitting, whereas consistently low R^2 values across both datasets suggest underfitting. A well-optimized model is defined by high and closely matched R^2 values for both training and testing, signifying robust generalization ability. As presented in Table 4, the MLP model achieved an R^2 of 0.99 for the training dataset and 0.983 for the testing dataset, complemented by low RMSE (0.0118), MAE (0.0186), and MRE (1.8%). These outcomes validate that the developed MLP model delivers precise PEC predictions and exhibits excellent generalization performance across unseen data.

Table 4. Performance metric values of different models for PEC prediction.

Predict Variable	Model	R^2_{train}	R^2_{test}	RMSE	MAE	MRE (%)
PEC	MLP	0.99	0.983	0.118	0.0186	1.8

Figure 12 compares the predicted and measured PEC values on various datasets. The orange dashed line denotes the 1:1 reference (ideal agreement), i.e., perfect predictions would lie exactly on this line. The green markers indicate the model outputs. As shown in Figure 12, the MLP predictions exhibit close agreement with the ground truth, with most points tightly clustered around the 1:1 line, demonstrating strong predictive accuracy and good generalization on unseen data. Minor deviations from the reference line are observed only in limited value ranges, implying slightly larger local errors, while the overall distribution remains compact and near-linear, indicating stable prediction performance.

**Figure 12.** Comparison of predicted and measured PEC values across various datasets: (a) training dataset results; (b) validation dataset results; (c) test dataset results; (d) test R^2 of MLP.

3.4. Analysis of Parameter Optimization and Corresponding Outcomes

This section employs the trained MLP model as the surrogate predictor for PEC due to its superior predictive accuracy. A GA is then used to search for the optimal parameter combination within the prescribed bounds. The GA uses a population size of 50, a maximum of 100 generations, a crossover probability of 0.8, and a mutation probability of 0.05. Since the thermal conductivity (k) and specific heat capacity (C_p) exert negligible influence on pressure drop, the optimization is restricted to five variables: Re , μ , K_F , F , and ρ , with ranges of $20.42 \leq Re \leq 149.28$, $998.2 \leq \rho \leq 1142.9$, $0.001677 \leq \mu \leq 0.01003$, $0 \leq K_F \leq 1.147 \times 10^{-9}$, and $0 \leq F \leq 0.0957$. During the evolution process, the trained MLP

repeatedly predicts PEC for each candidate solution, and the GA iteratively updates the population toward the optimum.

Based on the MLP-GA optimization results, Table 5 presents the optimized parameter combinations along with their corresponding PEC values. The final optimized parameters identified for this study are as follows: the Reynolds number (Re) is 22.1, the density (ρ) is 1137.4 kg/m^3 , the dynamic viscosity (μ) is $0.001005 \text{ Pa}\cdot\text{s}$, the Forchheimer coefficient (K_F) is $1.47 \times 10^{-8} \text{ m}$, and the friction factor (F) is 0.0002985. Using these optimized parameters, the PEC value reached 2.88, indicating a notable enhancement in the system's comprehensive performance through the effective balancing of heat transfer efficiency and pressure drop. Subsequent CFD simulations using these parameters yielded a PEC of 2.86, with a 0.7% error, further validating the reliability and accuracy of the optimization results.

Table 5. Optimization results: parameter combinations and PEC values.

Result	Re	$\rho \text{ (kg/m}^3\text{)}$	$\mu \text{ (Pa}\cdot\text{s)}$	$K_F \text{ (10}^{-8}\cdot\text{m)}$	F	PEC (GA)	PEC (CFD)
Optimized Case	22.1	1137.4	0.001005	1.47	0.0002985	2.88	2.86

3.5. Thermal–Hydraulic Performance Assessment of the Cooling System

To validate the optimized design, a numerical simulation was conducted on the battery pack integrated with the MFMCP cooling system, using the optimal parameter set listed in Table 5. Figure 13 presents a comparative analysis of the steady temperature distributions of the battery pack under identical pumping power conditions, achieved with two distinct cooling-plate configurations: (a) the conventional MCP and (b) the proposed MFMCP. As shown in Figure 13a, the battery pack's maximum surface temperature reaches 308.33 K when using the conventional MCP design. By comparison, the MFMCP design presented in Figure 13b achieves notably better thermal management, lowering the peak temperature to 304.10 K while also ensuring a much more even temperature profile throughout the battery assembly. Moreover, the high-temperature region in the MFMCP is notably smaller compared to the MCP, clearly indicating the enhanced heat dissipation capability brought by the inclusion of metal foam, which significantly improves thermal uniformity and overall cooling efficiency.

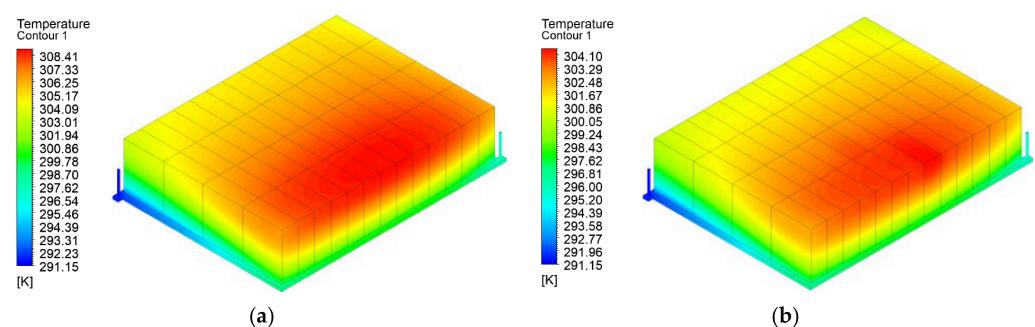


Figure 13. Comparative analysis of the steady temperature distributions of two battery packs: (a) MCP; (b) MFMCP.

To investigate the heat transfer performance of the MFMCP under realistic dynamic operating conditions of batteries, Figure 14 presents the time histories of the maximum battery temperature at three discharge rates (1C, 1.5C, and 2C), comparing the conventional MCP and the proposed MFMCP configurations. Across the full range of operating scenarios, the MFMCP sustains peak temperatures that are consistently reduced during the complete discharge process. This observed thermal behavior demonstrates the MFMCP system's superior capability in regulating and managing heat. Specifically, the maximum temperature

reductions in MFMCP relative to the MCP are 4.25 K at 1C, 2.96 K at 1.5C, and 3.93 K at 2C, respectively. Taken together, both steady and transient simulation results demonstrate that the MFMCP possesses robust heat dissipation capacity, ensuring that the maximum battery temperature remains below 318.15 K across all tested discharge scenarios.

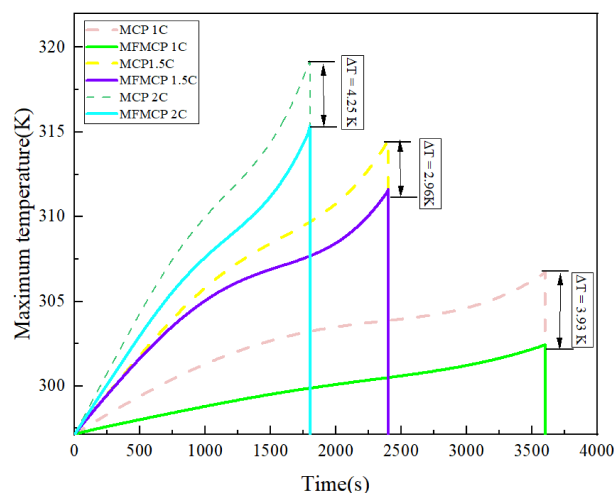


Figure 14. Temporal evolution of maximum temperature of two battery packs at three discharge rates.

4. Conclusions

This study investigates how varying structural parameters of copper metal foam and different volume fractions of Al_2O_3 nanofluid influence the thermal and flow performance in the MFMCP. Using scanning electron microscopy (SEM), the microstructural properties, including pore diameter and ligament thickness, were measured, providing essential input data for numerical simulations conducted with the LTE model and the Brinkman–Darcy–Forchheimer flow model. These simulations assessed the thermal–hydraulic performance of four MFMCP overflow unit configurations under equivalent heat flux conditions, with performance evaluated through the PEC method. An MLP model was also developed to predict PEC values, and a GA was employed to optimize key design parameters. The optimized MFMCP design was integrated into a full-scale battery pack and simulated under various discharge rates. The results demonstrated that all MFMCP designs enhanced heat transfer performance, with the maximum surface temperature decreasing by up to 15 K compared to the traditional design. However, this improvement came with increased flow resistance. Among the configurations, Case 2 consistently showed the highest PEC values (2.57 at $\text{Re} = 60$), while Case 4 had the lowest. The use of Al_2O_3 nanofluid further reduced the heating surface temperature, but also increased flow resistance, lowering the PEC. Higher nanofluid volume fractions led to further PEC reductions for the same inlet Reynolds number. Optimization with the GA achieved a PEC of 2.88, demonstrating the reliability of the optimization approach. A thermal–hydraulic analysis of the optimized MFMCP cooling system revealed its superior performance, with a lower maximum temperature (304.35 K) compared to the MCP (308.33 K) and a more uniform temperature distribution. Transient simulations showed that, at discharge rates of 1C, 1.5C, and 2C, the MFMCP reduced the peak temperature by 4.25 K, 2.96 K, and 3.93 K, respectively, confirming its superior thermal management performance across varying operational conditions.

Author Contributions: Investigation, X.L., J.R. and H.L.; Conceptualization, J.R.; Methodology, X.L.; Software, B.X. and H.L.; Visualization, J.R.; Writing—original draft, J.R.; Formal analysis, B.X. and H.L.; Project administration, B.X.; Writing—review & editing, X.L. and Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Chengdu Engineering Corporation Limited, Power China, grant number P63024, Research on Coupled Operation of Hybrid Energy Storage for High-Penetration Renewable Energy Integration.

Data Availability Statement: The data that support the findings of this study are available from the corresponding authors upon reasonable request.

Acknowledgments: The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: Authors Xiang Li, Jun Ren and Benjun Xie were employed by the company Chengdu Engineering Corporation Limited, Power China. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Abbreviations

BTMS	battery thermal management system
MFMCP	metal foam manifold cold plate
PPI	pores per inch
LTE	local thermal equilibrium
PEC	performance evaluation criterion
MLP	multi-layer perceptron
GA	genetic algorithm
EVs	electric vehicles
AI	artificial intelligence
LSTM	long short-term memory
CNNs	convolutional neural networks
CFD	computational fluid dynamics
SEM	scanning electron microscopy
SOC	state of charge
DOD	depth of discharge
MAE	mean absolute error
MRE	mean relative error
RMSE	root mean squared error

References

1. Brouwer, A.S.; van den Broek, M.; Seebregts, A.; Faaij, A. Impacts of large-scale Intermittent Renewable Energy Sources on electricity systems, and how these can be modeled. *Renew. Sustain. Energy Rev.* **2014**, *33*, 443–466. [\[CrossRef\]](#)
2. Mortaz, E.; Valenzuela, J. Evaluating the impact of renewable generation on transmission expansion planning. *Electr. Power Syst. Res.* **2019**, *169*, 35–44. [\[CrossRef\]](#)
3. Ali, B. Comparative assessment of the feasibility for solar irrigation pumps in Sudan. *Renew. Sustain. Energy Rev.* **2018**, *81*, 413–420. [\[CrossRef\]](#)
4. Zapata, S.; Castaneda, M.; Garces, E.; Franco, C.J.; Dyner, I. Assessing security of supply in a largely hydroelectricity-based system: The Colombian case. *Energy* **2018**, *156*, 444–457. [\[CrossRef\]](#)
5. Lou, X.; Zhang, Q.; Zou, S.; Meng, F.; Yue, C.; Zhou, H.; Wen, L.; Long, G. Field study on the temperature uniformity of containerized batteries using a two-phase liquid cooling system under mismatched conditions. *Int. J. Refrig.* **2025**, *170*, 85–97. [\[CrossRef\]](#)
6. Shanmugam, M.; Maganti, L.S. Multi-objective optimization of parallel microchannel heat sink with inlet/outlet U, I, Z type manifold configuration by RSM and NSGA-II. *Int. J. Heat Mass Transf.* **2023**, *201*, 123641. [\[CrossRef\]](#)
7. Zhao, Y.; Wang, D.; Yang, D.; Wei, L.; Liu, B.; Wang, X.; Chen, G.; Wei, Y. Superior Mg²⁺ storage properties of VS₂ nanosheets by using an APC-PP14Cl/THF electrolyte. *Energy Storage Mater.* **2019**, *23*, 749–756. [\[CrossRef\]](#)
8. Zhao, J.; Rao, Z.; Li, Y. Thermal performance of mini-channel liquid cooled cylinder based battery thermal management for cylindrical lithium-ion power battery. *Energy Convers. Manag.* **2015**, *103*, 157–165. [\[CrossRef\]](#)
9. Karimi, G.; Dehghan, A.R. Thermal analysis of high-power lithium-ion battery packs using flow network approach. *Int. J. Energy Res.* **2014**, *38*, 1793–1811. [\[CrossRef\]](#)

10. Yang, H.; Wang, Z.; Li, M.; Ren, F.; Feng, Y. A manifold channel liquid cooling system with low-cost and high temperature uniformity for lithium-ion battery pack thermal management. *Therm. Sci. Eng. Prog.* **2023**, *41*, 101857. [\[CrossRef\]](#)
11. Wang, Y.; Meng, T.; Chu, W. Thermal management and phase change heat transfer characteristics of LiFePO₄ batteries by cooling phase change materials. *Therm. Sci.* **2022**, *26*, 3881–3896. [\[CrossRef\]](#)
12. Le, Q.; Shi, Q.; Liu, Q.; Yao, X.; Ju, X.; Xu, C. Numerical investigation on manifold immersion cooling scheme for lithium ion battery thermal management application. *Int. J. Heat Mass Transf.* **2022**, *190*, 122750. [\[CrossRef\]](#)
13. Wang, Y.; Yu, Y.; Jing, Z.; Wang, C.; Zhou, G.; Zhao, W. Thermal performance of lithium-ion batteries applying forced air cooling with an improved aluminium foam heat sink design. *Int. J. Heat Mass Transf.* **2021**, *167*, 120827. [\[CrossRef\]](#)
14. Liu, Z.; Zhao, H.; Qiu, Y.; Zeng, H.; Dong, X. Numerical analysis of topology-optimized cold plates for thermal management of battery packs. *Appl. Therm. Eng.* **2024**, *238*, 121983. [\[CrossRef\]](#)
15. Yang, S.; Li, J.; Cao, B.; Wu, Z.; Sheng, K. Investigation of Z-type manifold microchannel cooling for ultra-high heat flux dissipation in power electronic devices. *Int. J. Heat Mass Transf.* **2024**, *218*, 124792. [\[CrossRef\]](#)
16. Zhan, S.; Cheng, Z.; Yin, Y.; Yu, C.; Zhao, C. Effect of inlet and outlet positions on heat dissipation performance of lithium-ion battery cold plates: An analysis based on topology optimization. *Int. J. Heat Mass Transf.* **2023**, *215*, 124436. [\[CrossRef\]](#)
17. Keyinci, S.; Ilinčić, P.; Tosun, E.; Uzun, M.; Yakaryilmaz, A.C.; Ozcanli, M. Design and performance analysis of a curved channel liquid cooling system for battery thermal management. *Therm. Sci. Eng. Prog.* **2025**, *63*, 103690. [\[CrossRef\]](#)
18. Mo, X.; Zhi, H.; Xiao, Y.; Hua, H.; He, L. Topology optimization of cooling plates for battery thermal management. *Int. J. Heat Mass Transf.* **2021**, *178*, 121612. [\[CrossRef\]](#)
19. Chen, F.; Wang, J.; Yang, X. Topology optimization design and numerical analysis on cold plates for lithium-ion battery thermal management. *Int. J. Heat Mass Transf.* **2022**, *183*, 122087. [\[CrossRef\]](#)
20. Ji, H.; Luo, T.; Dai, L.; He, Z.; Wang, Q. Topology design of cold plates for pouch battery thermal management considering heat distribution characteristics. *Appl. Therm. Eng.* **2023**, *224*, 119940. [\[CrossRef\]](#)
21. Ki, S.; Lee, J.; Kim, S.; Seong, J.; Shim, J.; Oh, S.; Cho, S.; Bang, S.; Seo, D.; Kim, J.; et al. An energy-efficient battery thermal management system incorporating a porous metal-based multiscale flow manifold. *Energy Convers. Manag.* **2022**, *269*, 116147. [\[CrossRef\]](#)
22. Keyhani-Asl, A.; Perera, N.; Lahr, J.; Hasan, R. Numerical analysis of copper foam-enhanced hybrid battery thermal management systems for lithium-ion batteries: Advancing energy density and thermal control. *Appl. Therm. Eng.* **2025**, *278*, 127183. [\[CrossRef\]](#)
23. Rabiei, M.; Gharehghani, A.; Andwari, A.M. Enhancement of battery thermal management system using a novel structure of hybrid liquid cold plate. *Appl. Therm. Eng.* **2023**, *232*, 121051. [\[CrossRef\]](#)
24. Dong, H.; Chen, X.; Yan, S.; Wang, D.; Han, J.; Guan, Z.; Cheng, Z.; Yin, Y.; Yang, S. Multi-objective optimization of lithium-ion battery pack thermal management systems with novel bionic lotus leaf channels using NSGA-II and RSM. *Energy* **2025**, *314*, 134226. [\[CrossRef\]](#)
25. Tartibu, L.K. Multi-objective Optimization of Multi-channel Cold Plate Under Intermittent Pulsating Flow Using Jaya Algorithm. In *Multi-Objective Optimization Techniques in Engineering Applications: Advanced Methods for Solving Complex Engineering Problems*; Springer: Berlin/Heidelberg, Germany, 2025; pp. 205–237.
26. Lin, X.-W.; Shi, M.-Y.; Zhou, Z.-F.; Chen, B.; Lu, Y.-J.; Jing, D.-W. Multi-objective topology optimization design of liquid-based cooling plate for 280 Ah prismatic energy storage battery thermal management. *Energy Convers. Manag.* **2025**, *325*, 119440. [\[CrossRef\]](#)
27. Zheng, A.; Gao, H.; Jia, X.; Cai, Y.; Yang, X.; Zhu, Q.; Jiang, H. Deep learning-assisted design for battery liquid cooling plate with bionic leaf structure considering non-uniform heat generation. *Appl. Energy* **2024**, *373*, 123898. [\[CrossRef\]](#)
28. Ebbs-Picken, T.; Da Silva, C.M.; Amon, C.H. Hierarchical thermal modeling and surrogate-model-based design optimization framework for cold plates used in battery thermal management systems. *Appl. Therm. Eng.* **2024**, *253*, 123599. [\[CrossRef\]](#)
29. Topcu, G.; Ercetin, U.; Timuralp, C. CFD Analysis of Liquid-Cooled Heatsink Using Nanofluids in Computer Processors. *Sci. Iran.* **2023**, *31*, 1916–1925.
30. Khan, S.A.; Siddiqui, M.A.; Asjad, M.; Khan, Z.A.; Husain, S. CFD simulation and optimization of natural convection in a vertical annulus with nanofluids. *Int. J. Therm. Sci.* **2023**, *185*, 108079. [\[CrossRef\]](#)
31. Najafabadi, M.K.; Klazly, M.; Sayfidinov, O.; Hriczó, K.; Bognár, G. CFD study of heat transfer enhancement for Al₂O₃-turbine oil nanofluid flow in a pipe. *AIP Conf. Proc.* **2023**, *2849*, 160006. [\[CrossRef\]](#)
32. Rao, B.N.; Sreedhar, T. Heat transfer analysis of nanofluids for fixed volume fraction of pipe in pipe heat exchanger using CFD. *Mater. Today Proc.* **2023**; in press. [\[CrossRef\]](#)
33. Soheli, M.R.; Khaleduzzaman, S.S.; Saidur, R.; Hepbasli, A.; Sabri, M.F.M.; Mahbubul, I.M. An experimental investigation of heat transfer enhancement of a minichannel heat sink using AlO-HO nanofluid. *Int. J. Heat Mass Transf.* **2014**, *74*, 164–172. [\[CrossRef\]](#)
34. Moraveji, M.K.; Ardehali, R.M. CFD modeling (comparing single and two-phase approaches) on thermal performance of Al₂O₃/water nanofluid in mini-channel heat sink. *Int. Commun. Heat Mass Transf.* **2013**, *44*, 157–164. [\[CrossRef\]](#)

35. Ali, A.M.; Angelino, M.; Rona, A. Numerical analysis on the thermal performance of microchannel heat sinks with Al₂O₃ nanofluid and various fins. *Appl. Therm. Eng.* **2021**, *198*, 117458. [[CrossRef](#)]
36. Lv, C.W.; Li, W.; Du, J.X.; Liang, J.L.; Yang, H.Z.; Zhu, Y.G.; Ma, B.J. Experimental investigation of permeability and Darcy–Forchheimer flow transition in metal foam with high pore density. *Exp. Therm. Fluid Sci.* **2024**, *154*, 111149. [[CrossRef](#)]
37. Hung, T.C.; Huang, Y.X.; Yan, W.M. Thermal performance analysis of porous-microchannel heat sinks with different configuration designs. *Int. J. Heat Mass Transf.* **2013**, *66*, 235–243. [[CrossRef](#)]
38. Vajjha, R.S.; Das, D.K. A review and analysis on influence of temperature and concentration of nanofluids on thermophysical properties, heat transfer and pumping power. *Int. J. Heat Mass Transf.* **2012**, *55*, 4063–4078. [[CrossRef](#)]
39. Pan, Y.-H.; Zhao, R.; Nian, Y.-L.; Cheng, W.-L. Numerical study on heat transfer characteristics of a pin–fin staggered manifold microchannel heat sink. *Appl. Therm. Eng.* **2023**, *219*, 119436. [[CrossRef](#)]
40. Huo, Y.; Rao, Z. The numerical investigation of nanofluid based cylinder battery thermal management using lattice Boltzmann method. *Int. J. Heat Mass Transf.* **2015**, *91*, 374–384. [[CrossRef](#)]
41. Ranjbar, A.M.; Pouransari, Z.; Siavashi, M. Improved design of heat sink including porous pin fins with different arrangements: A numerical turbulent flow and heat transfer study. *Appl. Therm. Eng.* **2021**, *198*, 117519. [[CrossRef](#)]
42. Kaviani, M. Laminar-Flow through a Porous Channel Bounded by Isothermal Parallel Plates. *Int. J. Heat Mass Transf.* **1985**, *28*, 851–858. [[CrossRef](#)]
43. Alfellag, M.A.; Ahmed, H.E.; Jehad, M.G.; Hameed, M. Assessment of heat transfer and pressure drop of metal foam-pin-fin heat sink. *Int. J. Therm. Sci.* **2021**, *170*, 107109. [[CrossRef](#)]
44. Jarrett, A.; Kim, I.Y. Design optimization of electric vehicle battery cooling plates for thermal performance. *J. Power Sources* **2011**, *196*, 10359–10368. [[CrossRef](#)]
45. Li, Y.T.; Gong, L.; Xu, M.H.; Joshi, Y. Hydraulic and thermal performances of metal foam and pin fin hybrid heat sink. *Appl. Therm. Eng.* **2020**, *166*, 114665. [[CrossRef](#)]
46. Xu, J.; Chen, Z.L.; Qin, J.; Pan, M.Q. A lightweight and low-cost liquid-cooled thermal management solution for high energy density prismatic lithium-ion battery packs. *Appl. Therm. Eng.* **2022**, *203*, 117871. [[CrossRef](#)]
47. Li, W.L.; Wang, Y.W.; He, B.; Guo, J.; Ju, G.D.; Yu, Z.; Chen, Z.R.; Jiang, F.M. Influence of structural parameters on immersion cooling performance of a 1P52S 280 Ah prismatic LiFePO₄ battery pack. *Appl. Therm. Eng.* **2025**, *261*, 125185. [[CrossRef](#)]
48. Khaboshan, H.N.; Jalilantabar, F.; Abdullah, A.A.; Panchal, S.; Azarinia, A. Parametric investigation of battery thermal management system with phase change material, metal foam, and fins; utilizing CFD and ANN models. *Appl. Therm. Eng.* **2024**, *247*, 123080. [[CrossRef](#)]
49. Liu, X.; Zhang, J.H.; Li, Z.; Gu, S.M.; Zhao, L.; Liu, B. Design and modelling of multiple-air-chamber pneumatic soft bending actuators. *Int. J. Hydromechatronics* **2025**, *8*, 29–50. [[CrossRef](#)]
50. Lambora, A.; Gupta, K.; Chopra, K. Genetic algorithm-A literature review. In *Proceedings of the 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 14–16 February 2019*; IEEE: Piscataway, NJ, USA, 2019.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.