

Article

Thermal Modeling of a Cylindrical Lithium-Ion Battery in 3D with the Taguchi Optimization Method

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Abstract

Thermal management is critical for the safety, performance, and life cycle of lithium-ion (Li-ion) batteries. This study aims to determine the optimum settings and contribution levels of key parameters affecting the operating temperature of a three-dimensional (3D) thermal model of a cylindrical Li-ion battery. A Taguchi L9 orthogonal array was designed with four: (A) base fluid and (B) Al_2O_3 volume fraction ($\Phi\text{-Al}_2\text{O}_3$) of the nanofluid coolant, (C) battery–battery distance, and (D) inlet temperature (T_{inlet}), each varied on 3-level control factors. To minimize the maximum battery temperature (T_{max}), the “smaller-is-better” signal-to-noise (S/N) ratio approach and Analysis of Variance (ANOVA) were applied. The S/N analysis and ANOVA revealed that the base fluid (A: 44.96%) and T_{inlet} (D: 36.00%) were the most dominant factors influencing the T_{max} . The optimal design identified by the Taguchi method (A3-B3-C3-D1) successfully reduced the T_{max} to 33.5 °C, a 29.0 °C reduction compared with the initial air-cooled reference model (62.5 °C). Furthermore, the maximum temperature rise during the 2100 s operation was reduced by approximately 62%. This optimal T_{max} of 33.5 °C was even lower than the best result in the L9 array (35.5 °C), validating the strong predictive capability of the method.

Keywords: BTMS; Taguchi method; volume fraction; nanofluid; battery–battery distance; T_{inlet}

1. Introduction

Batteries are widely promoted as a ‘green’ alternative intended to liberate society from fossil fuel reliance. However, pushing the limits of batteries reveals their significant drawbacks: they are slow to charge, hold finite energy, offer limited runtime, and have a short operational life of just a few hundred cycles before turning into a disposal burden [1]. Battery Thermal Management Systems (BTMS) have important tasks, such as keeping the battery’s T_{max} below a certain value and minimizing the temperature differences within the battery pack. These tasks help to extend the lifespan of the battery packs, ensure the highest possible performance throughout the battery’s life, and maintain the safety of the battery packs [2]. Among BTMS solutions, air cooling systems are widely used due to their advantages of low cost, simple structure, and light weight. The thermal behavior of an air-cooled battery pack depends on the pack’s geometric design (e.g., battery–battery distance) and operational conditions (e.g., cooling air velocity and ambient temperature). However, the individual and combined effects of these factors on battery temperature are complex. It is critical for designers to know which parameter has the most dominant effect on temperature control in order to direct optimization efforts and costs appropriately.



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S. Ozbektas et al. focused on developing models capable of more accurate temperature prediction for Li-ion batteries. They analyzed four main test parameters that could affect the battery model's accuracy: Pulse time gap, discharge pulse time, discharge pulse C rate, and rest time. Using the Taguchi method, this study revealed which test parameters the battery model is most sensitive to and statistically proved that the discharge C-rate is the most critical factor [3]. S. Sudhakaran et al. focused on systems using phase change materials (PCM) to cool Li-ion batteries. They tested four different parameters at four different levels. These were: PCM material, PCM thickness, additive (copper foam additive used to improve low thermal conductivity, which is the main problem of PCMs), and heat transfer coefficient. They found that the two most effective factors in controlling battery temperature were, by far, the type of PCM material and its thickness [4]. Sharma et al. studied three main control factors affecting the system's performance to design a new hybrid cooling system and find the settings at which it operates most efficiently: Flow rate, coolant ratio (a mixture of ethylene glycol (EG) and water), and fan speed. Flow rate and coolant ratio (the percentage of glycol in the mixture) were identified as the most critical factors affecting system efficiency. Fan speed was found to have very little effect on performance or to be at a 'static level' [5]. O. Yetik et al. numerically investigated a liquid cooling system using nanofluid for the thermal management of Li-ion batteries. They modeled a battery module consisting of 15 series-connected prismatic Li-ion cells. As the coolant, they used a nanofluid obtained by mixing Fe_2O_3 nanoparticles with the base fluid, engine oil (EO). They investigated four main control factors at four different levels: Coolant inlet velocity (V_{inlet}), nanoparticle mixing ratio, ambient temperature, and discharge rate. Factor Effects: As the discharge rate increased, the battery temperature also increased, as expected. As the coolant V_{inlet} increased, the battery temperature decreased. As the nanoparticle mixing ratio increased (i.e., as the nanofluid density increased), the battery temperature decreased and the cooling performance improved. C-rate (47.82%) and ambient temperature (35.96%) were the two most dominant factors on the T_{max} , while the effect of the mixing ratio remained at only 3.28%. Regarding the effect on uniformity, C-rate (54.13%) and V_{inlet} (25.72%) were the most dominant factors, while the effect of the mixing ratio was only 2.24% [6]. Hosseinzadeh et al. statistically demonstrated using the ANOVA method that there is a fundamental trade-off between energy and power in battery design; thick electrodes and small particles are critical for energy, whereas thin electrodes and a high C-rate are critical for power [7]. J. Ye et al. demonstrated that a hybrid system combining air and liquid cooling performs better than traditional systems and specifically identified that the air flow rate plays a more dominant role than the liquid flow rate in improving the system's overall efficiency (entropy generation) [8]. H. Fayaz et al. emphasize that there is no single solution for optimizing a battery's thermal performance; instead, many different parameters (cooling type, flow rate, battery spacing, material, etc.) must be co-optimized depending on the application's requirements. They noted that air cooling is simple and cheap but has low efficiency. They highlighted studies indicating that optimizing air flow channels and battery layout is essential for improvement. They stated that liquid cooling (especially mini-channel cooling plates) is much more efficient at dissipating high heat but adds complexity and cost. They determined that optimizing channel design and fluid flow rate is critical for the best performance. They emphasized studies showing that the arrangement of battery cells in the pack (e.g., inline, staggered) and the amount of spacing between them directly affect both cooling efficiency and temperature homogeneity [9]. As a result of the study by S. Chavan et al., water cooling provided much lower battery temperatures in all channel designs compared with air cooling (e.g., in the curved channel, water was 304.44 K, while air was 305.03 K) [10]. According to the results found by S. Birinci et al., increasing the velocity of the coolant allowed more heat to be

extracted from the system. Therefore, as the flow rate increased, both the battery $T_{\max}$ and the temperature difference between batteries decreased significantly. As the temperature of the coolant water increased (e.g., from 15 °C to 45 °C), the $T_{\max}$ reached by the battery also increased, as expected. In summary, this study showed that the most effective way to reduce the $T_{\max}$ battery in liquid cooling is to increase the flow rate, but the coolant T_{inlet} is also an important factor for achieving temperature homogeneity, and a balance (trade-off) must be established between these two parameters [11]. J. Mustafa revealed that when cooling multiple battery packs, enlarging the inlet channel cools the batteries better, but both enlarging the inlet channel and increasing the spacing between the packs significantly increase the fan power (energy consumption) required for cooling [12]. Y. Zhang et al. found that increasing the air V_{inlet} significantly reduced the $T_{\max}$, while increasing the horizontal distance between the batteries raised the $T_{\max}$ but improved homogeneity by reducing the temperature difference [13]. S. Park et al. found that the influence of the cooling plate outer width factor on the $T_{\max}$ decreased as the discharge rate increased [14]. All the mentioned studies reveal a complex scenario with hard-to-identify leading factors for battery thermal management.

The objective of this study is to perform an optimization study on a 3D electrochemical-thermal coupled model of a cylindrical Li-ion battery, developed in COMSOL Multiphysics. The main novelty of this study is the first-time evaluation of multi-disciplinary factors such as nanofluid concentration and physical battery arrangement in this specific configuration, applying the Taguchi optimization method to a 3D electrochemical-thermal coupled cylindrical lithium-ion battery model developed in COMSOL Multiphysics. To minimize the battery's $T_{\max}$, the Taguchi L9 orthogonal array methodology was utilized. Four main control factors (base fluid and $\Phi\text{-Al}_2\text{O}_3$ of the nanofluid coolant, battery–battery distance, T_{inlet}) were investigated at three levels each. Using Minitab software, ANOVA was applied to determine the statistical percentage contribution of each parameter to the battery $T_{\max}$. Concurrently, S/N ratio analysis was used to identify the optimum setting combination for the lowest and most stable temperature. This study aims to reveal which design and operational parameters should be prioritized in thermal management.

2. Materials and Methods

2.1. Physical and Chemical Properties

This study presents a model of a cylindrical 18,650 battery (18 mm in diameter and 65 mm in height), which couples a one-dimensional electrochemical model with a 3D simulation of its thermal behavior. In this study, the electrochemical heat generation of the battery was modeled using the physics-based Doyle–Fuller–Newman (DFN) framework, also known as the Pseudo-2D (P2D) model. The key geometric and electrochemical parameters [15] used in the DFN model are summarized in Table A2. The DFN model calculates the total volumetric heat source by resolving the fundamental electrochemical equations (ohmic, polarization, and entropic heating), which is then dynamically coupled to the 3D thermal model. This 3D thermal model also incorporates a dedicated flow domain for a cooling fluid, enabling the fluid's motion to affect the heat transfer rate, which is coupled using the Nonisothermal Flow Multiphysics interface. A one-way coupling approach is adopted due to the assumption that the fluid's properties remain independent of temperature. However, it is crucial to note that the interaction between the 1D electrochemical model and the 3D thermal domain employs a rigorous two-way non-isothermal feedback loop. While the fluid properties are kept constant, the transient local temperature computed in the 3D domain dynamically updates the temperature-dependent electrochemical parameters (e.g., solid/liquid diffusion coefficients and reaction kinetics) in the 1D model via Arrhenius expressions. This continuously alters the internal resistance and heat generation

rates as the battery heats up or cools down. The underlying cell model, built with the Li-ion Battery interface, is composed of a 55 μm negative porous electrode (Li_xC_6 MCMB), a 30 μm separator, and a 55 μm positive porous electrode (LiFePO_4). The 3D thermal model (see Figure 1), which is constructed using the Heat Transfer in Solids and Fluids interface, represents temperature as the average temperature of the active battery material, calculated via a nonlocal integration coupling.

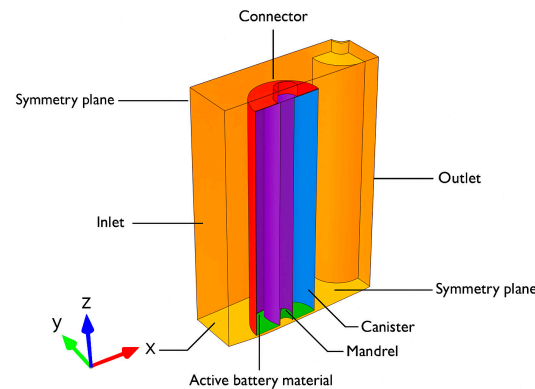


Figure 1. Geometry of the thermal model [15].

The model's solution is achieved in three stages. Initially, a steady-state computation determines the laminar flow field at 298.15 K, which is also the battery's starting temperature. The second stage establishes the initial electrochemical potentials ($t = 0$). Finally, a time-dependent study is run for the coupled problem. This simulation uses boundary conditions including 1 atm outlet pressure, no-slip conditions on battery walls, and symmetry conditions on the specified planes [15].

2.2. Numerical Method

Thermal Modeling of a Cylindrical Lithium-ion Battery in 3D model in the COMSOL Multiphysics 6.0 Battery Design Module consists of two distinct components. The first is the 1D Cell Model, which is constructed using the Li-ion Battery interface as reported in [16], with its numerical model detailed in references [17,18]. To maintain the flow of the primary thermal optimization focus, the fundamental governing equations of the physics-based P2D electrochemical framework and the detailed formulation of the electrochemical heat generation sources are comprehensively provided in Appendix A. The second component is the 3D Thermal Model, which is developed using the Heat Transfer in Solids and Fluids interface. This 3D model, implemented in COMSOL Multiphysics, is the basis for the equations [15] discussed in Section 2.2.

This set of equations dictates the fluid dynamics of the cooling medium utilized in the battery thermal management system, predicated on the assumption of a steady, incompressible flow.

$$\rho(\mathbf{u} \cdot \nabla)\mathbf{u} = \nabla \cdot [-p\mathbf{I} + \mathbf{K}] + \mathbf{F} \quad (1)$$

$$\rho \nabla \cdot \mathbf{u} = 0 \quad (2)$$

- ρ : Density of the fluid (coolant).
- $\mathbf{u}$: Velocity vector of the fluid.
- ∇ : The Nabla operator, representing spatial derivatives (gradient, divergence).
- p : Pressure in the fluid.
- $\mathbf{I}$: The identity tensor.
- $\mathbf{K}$: The viscous stress tensor, defined below.
- $\mathbf{F}$: Volume force vector (e.g., gravity).

$$\mathbf{K} = \mu \left(\nabla \mathbf{u} + (\nabla \mathbf{u})^T \right) \quad (3)$$

- μ : Dynamic viscosity of the fluid (e.g., Pa·s). It is a measure of the fluid's resistance to flow.
- $\nabla \mathbf{u}$: The velocity gradient tensor.
- $(\nabla \mathbf{u})^T$: The transpose of the velocity gradient tensor.

This equation represents an essential boundary condition within fluid dynamics.

$$\mathbf{u} = 0 \quad (4)$$

A no-slip boundary condition is prescribed at the battery walls, as defined by this equation.

Equations (5) and (6) dictate the pressure-outlet boundary condition for the Laminar Flow interface, ensuring a constant pressure of 1 atm is sustained at the flow compartment's exit.

$$\mathbf{n}^T [-p\mathbf{I} + \mathbf{K}] \mathbf{n} = -\hat{p}_0 \quad (5)$$

$$\hat{p}_0 \leq p_0, \mathbf{u} \cdot \mathbf{t} = 0 \quad (6)$$

- $\mathbf{n}$: The unit vector normal (perpendicular) to the boundary, pointing outward from the fluid domain.
- $-p\mathbf{I} + \mathbf{K}$: This is the total stress tensor acting on the fluid. It combines the pressure stress ($-p\mathbf{I}$) and the viscous stress ($\mathbf{K}$).
- $-\hat{p}_0$: This is a prescribed external pressure acting on the boundary from the outside.

Equation (7) dictates the inlet velocity boundary condition for the flow domain.

$$\mathbf{u} = -U_0 \mathbf{n} \quad (7)$$

- $\mathbf{u}$: The fluid velocity vector at the boundary.
- U_0 : A constant value representing the speed or velocity magnitude.

Applied to the symmetry planes, Equations (8) and (9) dictate the boundary conditions necessary to model the repeating configuration of the battery pack.

$$\mathbf{u} \cdot \mathbf{n} = 0 \quad (8)$$

$$\mathbf{K}_n - (\mathbf{K}_n \cdot \mathbf{n}) \mathbf{n} = 0, \mathbf{K}_n = \mathbf{K} \mathbf{n} \quad (9)$$

- $\mathbf{K}$: The viscous stress tensor ($\mathbf{K} = \mu(\nabla \mathbf{u} + (\nabla \mathbf{u})^T)$).
- $\mathbf{K} \mathbf{n}$: The total viscous stress vector acting on the boundary.
- $(\mathbf{K} \mathbf{n} \cdot \mathbf{n}) \mathbf{n}$: The component of that stress that is normal to the boundary.

The Heat Transfer physics for the COMSOL battery model are described by these governing equations.

$$\rho C_p \mathbf{u} \cdot \nabla T + \nabla \cdot \mathbf{q} = Q + Q_{\text{ted}} \quad (10)$$

$$\mathbf{q} = -k \cdot \nabla T. \quad (11)$$

- $\rho C_p \mathbf{u} \cdot \nabla T$: Convective Heat Transfer.
 - ρ : Density of the material.
 - C_p : Specific heat capacity.
 - $\mathbf{u}$: Velocity vector field (from the Laminar Flow solution).
 - ∇T : Temperature gradient.

- $\nabla \cdot \mathbf{q}$: Conductive Heat Transfer (the divergence of the heat flux).
 - This term represents how heat diffuses through the materials due to temperature differences.
- $Q + Q_{ted}$: Heat Sources.
 - Q : The main heat source from the battery electrochemistry (Joule heating, reaction heat).
 - Q_{ted} : Thermo-electric dissipation (Joule heating from electric currents, often negligible in battery models compared with the electrochemical heating).
- $\mathbf{q}$: Heat flux vector (direction and magnitude of heat flow).
- k : Thermal conductivity of the material.
- ∇T : Temperature gradient.
- $- \text{sign}$: Indicates that heat flows from high temperature to low temperature.

The volumetric heat generation (Q) within the active battery material is computed by the 1D electrochemical model and coupled to the 3D thermal domain. This heat source accounts for both irreversible and reversible heat generation mechanisms based on the Bernardi equation. The irreversible heat source includes Joule heating, resulting from ohmic losses in the solid electrodes and electrolyte, and activation heating, which arises from the charge transfer overpotential at the electrode-electrolyte interfaces. The reversible heat (entropic heat) is calculated using the entropy coefficient of the specific electrode materials, accounting for the entropy changes during lithium-ion intercalation and deintercalation. These components are simultaneously solved within the Electrochemical Heating Multiphysics interface to provide a comprehensive thermal profile of the cell.

Equations (10) and (11) dictate the heat transfer mechanisms within the solid components, namely the active battery material, mandrel, and connector. Conversely, Equations (12) and (13) formulate the energy balance for the fluid domain (cooling air), with Equation (13) specifically utilizing the ideal gas law to model variations in fluid density.

$$\rho C_p \mathbf{u} \cdot \nabla T + \nabla \cdot \mathbf{q} = Q + Q_p + Q_{vd} \quad (12)$$

$$\rho = \frac{p_A}{R_s T} \text{ in ideal gas domains} \quad (13)$$

- Left Side—Heat Transport:
 - $\rho C_p \mathbf{u} \cdot \nabla T$: Convective heat transfer—heat carried by fluid flow.
 - $\nabla \cdot \mathbf{q}$: Conductive heat transfer—heat diffusion through materials.
- Right Side—Heat Sources:
 - Q : General heat source (from battery electrochemistry).
 - Q_p : Pressure work—heating from fluid compression/expansion.
 - Q_{vd} : Viscous dissipation—heating from fluid friction.
- ρ : Gas density (changes with temperature).
- ρ_A : Reference density at a reference state.
- R_s : Specific gas constant.
- T : Absolute temperature.

Equation (14) establishes a zero-heat-flux (adiabatic) boundary condition to thermally insulate the system from the ambient environment. This condition is enforced across all exterior walls of the fluid compartment, excluding the inlet, outlet, and symmetry boundaries.

$$-\mathbf{n} \cdot \mathbf{q} = 0 \quad (14)$$

Equation (15) introduces the volumetric heat source to the active battery material. It utilizes scaled electrochemical heat generation data from the 1D model to compute the transient temperature profile within the 3D domain.

$$Q = Q_0 \quad (15)$$

- Q : The heat flux (heat flow per unit area) at the boundary.
- Q_0 : A constant value specifying the magnitude of the heat flux.

Equation (16) establishes a fixed temperature boundary condition at the entrance of the flow compartment, ensuring that the incoming cooling air remains at a constant 298.15 K for the duration of the simulation.

$$T = T_0 \quad (16)$$

- T : The temperature at the boundary.
- T_0 : A constant value specifying the prescribed temperature.

This equation specifies a particular heat source term within the fluid flow model.

$$Q_{vd} = \tau : \nabla \mathbf{u} \quad (17)$$

- Q_{vd} : The heat generated per unit volume due to viscous dissipation.
- τ : The viscous stress tensor.
- $\nabla \mathbf{u}$: The velocity gradient tensor.

2.3. Validation with Experimental Data from the Literature

The numerical COMSOL air-cooled cylindrical battery model analyzed in this study is compared against the experimental model utilized by Panchal et al. [19]. This study used a commercial 18,650 cylindrical Li-ion battery (LiFePO₄/Graphite) as a baseline. Tests were conducted at a controlled 298 K with air cooling, using a high-precision battery tester and thermal data acquisition system. The cell underwent charge/discharge cycles between 2.0 V and 3.6 V via an A & D Bitrode cycler (Bitrode Corporation, St. Louis, MO, USA), with aluminum connectors applied to minimize terminal resistance. To track transient temperature profiles, 30-gauge T-type thermocouples (± 1 °C measurement uncertainty) were placed on the anode, cathode, and mid-surface. All thermal data was logged using a National Instruments NI-FP-TC-120 field point system (National Instruments, Austin, TX, USA) [19]. As shown in Figure 2, the temperature change (ΔT)–time curves for both the numerical and experimental models align well.

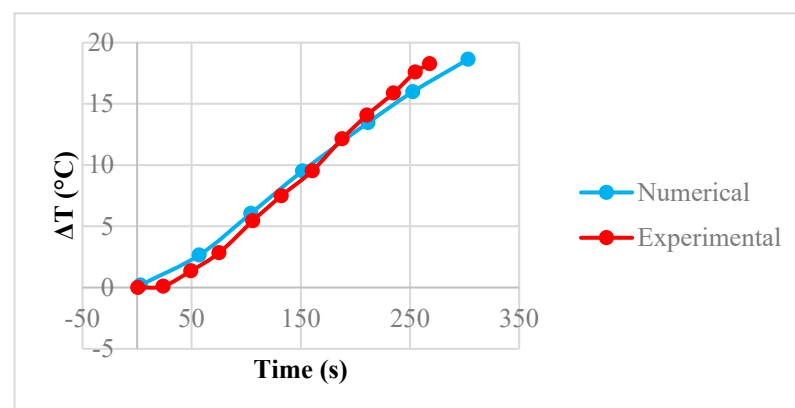


Figure 2. Experimental [19] and numerical ΔT (°C) profiles.

Air coolant was replaced with nanofluids to use their 3 different base fluid types and 3 different ratios of $\Phi\text{-Al}_2\text{O}_3$ as Taguchi parameters for the analyses.

2.4. Parameter Determination Using the Taguchi Optimization Method

The Taguchi method is an optimization method used not only for industrial applications but also for scientific studies, which enables reaching the optimum result in the shortest time by reducing the number of experiments or simulations. In this study, it was used to reach the optimum result in the shortest time by reducing the number of numerical analyses. In the Taguchi method, an orthogonal design is determined to find the most suitable combination among the selected parameters and their levels, and the optimization process is carried out through studies conducted on this design [20]. The Taguchi method uses the S/N ratio, which is equal to the ratio of the mean (signal) to the standard deviation (noise) during optimization. This ratio indicates the quality of a process or design [21].

In this study, since the aim is to reduce the maximum temperature ($T_{\max}$) reached by the battery, the “smaller-is-better” formulation was used in the Taguchi optimization method.

Under normal conditions, $3^4 = 81$ different numerical analyses must be performed to show the average effect of each level (level 1, 2, 3) of the four control factors studied on the $T_{\max}$ of the battery, thus constituting a full-factorial design of experiments. With the Taguchi optimization method, the total number of experiments was reduced, and the optimum design was reached in the shortest time. Table 1 shows the parameters used and the levels belonging to these parameters.

Table 1. Parameters and levels used in the optimization process.

Parameters	Level 1	Level 2	Level 3
Base Fluid (A)	EG	Ethylene Glycol–Water 30–70% vol. (EGW) [22]	W
$\Phi\text{-Al}_2\text{O}_3$ [23–25] (B)	2%	3%	5%
Battery–battery Distance (C)	$2.5 \times r_{\text{batt}}$ (9 mm)	$3 \times r_{\text{batt}}$	$3.5 \times r_{\text{batt}}$
T_{inlet} (D)	293.15 K	298.15 K	303.15 K

Rather than performing 81 numerical analyses, an L9 orthogonal array (Table 2) was created with Minitab Statistical Software 22 to be used in the analyses for 4 different parameters at 3 different levels.

Table 2. L9 orthogonal array design (4 factors, 3 levels).

Orthogonal Design	A	B	C	D
L1	1	1	1	1
L2	1	2	2	2
L3	1	3	3	3
L4	2	1	2	3
L5	2	2	3	1
L6	2	3	1	2
L7	3	1	3	2
L8	3	2	1	3
L9	3	3	2	1

3. Results

3D thermal model simulations were conducted for nine unique parameter configurations based on the Taguchi L9 orthogonal array design. The $T_{\max}$, designated as the study's primary response variable, was documented across all experimental setups and is detailed in Table 3.

Table 3. L9 orthogonal array design and resulting $T_{\max}$ values.

Orthogonal Design	A	B	C	D	$T_{\max}$ (°C)
L1	1	1	1	1	48.5
L2	1	2	2	2	48
L3	1	3	3	3	50
L4	2	1	2	3	46
L5	2	2	3	1	36
L6	2	3	1	2	45
L7	3	1	3	2	38.5
L8	3	2	1	3	47.5
L9	3	3	2	1	35.5

Analysis of the data presented in Table 3 demonstrates that variations in control factor levels profoundly influence the thermal behavior of the battery. The recorded $T_{\max}$ values span a broad spectrum, ranging from 35.5 °C to 50.0 °C, which corresponds to a substantial temperature differential of 14.5 °C.

- Minimum $T_{\max}$ (optimal condition): The lowest peak temperature of 35.5 °C was achieved under the L9 experimental setup (A3, B3, C2, D1). This optimal configuration utilizes water as the base fluid combined with a 5% volume fraction of Al_2O_3 , an inter-battery spacing of $3 \times r_{\text{batt}}$, and a coolant inlet temperature of 293.15 K. A comparable thermal response was noted in the L5 trial (A2, B2, C3, D1), which yielded a maximum temperature of 36.0 °C.
- Maximum $T_{\max}$ (critical condition): Conversely, the highest peak temperature of 50.0 °C occurred during the L3 experiment (A1, B3, C3, D3). This least favorable scenario involves ethylene glycol as the base fluid, a 5% Al_2O_3 volume fraction, an increased battery spacing of $3.5 \times r_{\text{batt}}$, and an elevated inlet temperature of 303.15 K.

The significant 14.5 °C discrepancy between the most favorable (L9) and least favorable (L3) operating conditions underscores the vital importance of proper parameter selection in the thermal optimization process.

To achieve the minimum $T_{\max}$, a “smaller-the-better” S/N analysis was employed. The responses for the S/N ratios, depicted in Table 4, outline the mean S/N values for all control factors (A, B, C, and D) across their respective levels. Following Taguchi's principles for a “smaller-the-better” target, the specific level that yields the highest S/N ratio is deemed optimal for any given factor.

A detailed assessment of the table yields the following optimal levels:

- Factor A (base fluid): The maximum S/N ratio (−32.08) was achieved at Level 3 (Water).
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): The peak S/N ratio (−32.68) was observed at Level 3 (5%).
- Factor C (battery–battery distance): The highest S/N ratio (−32.27) occurred at Level 3 ($3.5 \times r_{\text{batt}}$).
- Factor D (T_{inlet}): The maximum S/N ratio (−31.95) was recorded at Level 1 (293.15 K).

Table 4. Responses of S/N ratio for $T_{\max}$ (“smaller-is-better”).

Level	A	B	C	D
1	−33.77	−32.89	−33.44	−31.95
2	−32.48	−32.76	−32.63	−32.80
3	−32.08	−32.68	−32.27	−33.59
Delta	1.69	0.21	1.17	1.64
Rank	1	4	3	2

Derived from this analytical assessment, the optimal parametric configuration to effectively minimize the $T_{\max}$ is established as the A3-B3-C3-D1 setup.

Within the response table, the ‘Delta’ metric defined as the difference between the peak and minimum S/N ratios for any specific factor quantifies the relative impact of that parameter on the response variable ($T_{\max}$). The ‘Rank’ designation subsequently orders these factors according to the magnitude of their overall effect:

1. Factor A (base fluid): Delta = 1.69
2. Factor D (T_{inlet}): Delta = 1.64
3. Factor C (battery–battery distance): Delta = 1.17
4. Factor B ($\Phi\text{-Al}_2\text{O}_3$): Delta = 0.21

This established hierarchy clearly indicates that the selection of the base fluid and T_{inlet} are the predominant variables governing the efficiency of the battery cooling system. Conversely, the $\Phi\text{-Al}_2\text{O}_3$ (Factor B) was observed to exert the least significant influence on the $T_{\max}$ within the evaluated experimental boundaries.

To corroborate the conclusions drawn from the S/N ratio evaluation and to assess the direct impact of the control variables on the measured temperature data, the average $T_{\max}$ across all factor levels was scrutinized. The responses for means detailed in Table 5 outline the average peak temperatures recorded across levels 1, 2, and 3 for every tested parameter. Given the primary goal of minimizing $T_{\max}$, the optimal condition for each individual factor corresponds to the level that yields the lowest average temperature.

Table 5. Responses of means (raw data) for $T_{\max}$.

Level	A	B	C	D
1	48.83	44.33	47.00	40.00
2	42.33	43.83	43.17	43.83
3	40.50	43.50	41.50	47.83
Delta	8.33	0.83	5.50	7.83
Rank	1	4	3	2

An evaluation of the mean response table reveals the following:

- Factor A (base fluid): The minimum average temperature (40.50 °C) was recorded at Level 3 (Water—W).
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): The lowest mean temperature (43.50 °C) was observed at Level 3 (5%).
- Factor C (battery–battery distance): The minimum average temperature (41.50 °C) occurred at Level 3 ($3.5 \times r_{\text{batt}}$).
- Factor D (T_{inlet}): The lowest mean temperature (40.00 °C) was achieved at Level 1 (293.15 K).

These mean temperature findings serve as direct validation for the optimal parametric configuration (A3-B3-C3-D1) previously deduced via the S/N ratio analysis presented in Table 4.

Additionally, the 'Delta' metric within the means table calculated as the disparity between the maximum and minimum average $T_{\max}$ for any given variable illustrates the absolute magnitude of that factor's impact on T_{inlet} . The parameters are subsequently ordered in the 'Rank' column based on this degree of influence:

1. Factor A (base fluid): Delta = 8.33 °C
2. Factor D (T_{inlet}): Delta = 7.83 °C
3. Factor C (battery–battery distance): Delta = 5.50 °C
4. Factor B ($\Phi\text{-Al}_2\text{O}_3$): Delta = 0.83 °C

This hierarchical sequence aligns with the ranking established by the previous S/N ratio evaluation (1-A, 2-D, 3-C, 4-B). Both analytical methodologies uniformly confirm that the selection of the base fluid (Factor A) exerts the most dominant influence on the $T_{\max}$, closely followed by the T_{inlet} (Factor D). Conversely, the $\Phi\text{-Al}_2\text{O}_3$ (Factor B) yields a substantially less pronounced impact relative to the other investigated parameters.

To visually assess the influence of the control parameters (A, B, C, and D) on the battery's $T_{\max}$, a main effects plot was constructed in accordance with the Taguchi methodology. Illustrated in Figure 3, this chart serves as the graphical counterpart to the response table for means (detailed earlier in Table 5). The vertical axis denotes the mean $T_{\max}$, whereas the horizontal axis maps the distinct operational levels (1, 2, and 3) assigned to each variable.

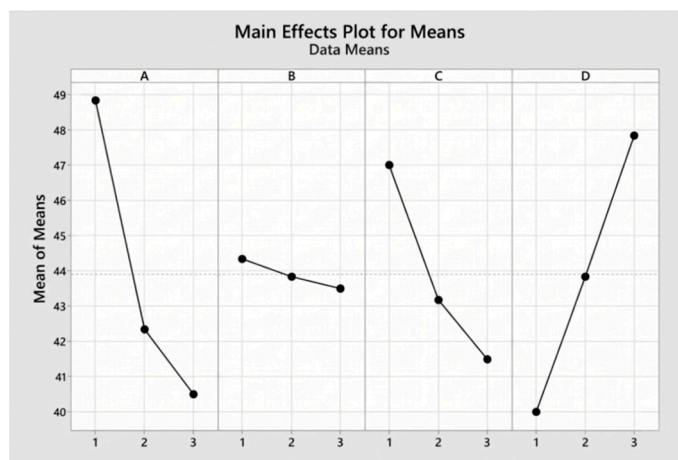


Figure 3. Main effects plot for means of $T_{\max}$ ((A) base fluid; (B) $\Phi\text{-Al}_2\text{O}_3$; (C) battery–battery distance; (D) T_{inlet}).

Given the primary goal of minimizing the $T_{\max}$, the optimal condition for any specific factor corresponds to the lowest plotted point on its respective trend line:

- Factor A (base fluid): The minimum mean temperature is achieved at Level 3 (Water).
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): The lowest mean temperature is observed at Level 3 (5%).
- Factor C (battery–battery distance): The minimum mean temperature is recorded at Level 3 ($3.5 \times r_{\text{batt}}$).
- Factor D (T_{inlet}): The lowest mean temperature is achieved at Level 1 (293.15 K).

This graphical evaluation definitively identifies the A3-B3-C3-D1 configuration as the optimal setup for minimizing $T_{\max}$, thereby reinforcing the analytical conclusions previously derived from the data in Tables 4 and 5.

Moreover, the gradient (or slope) of the plotted lines serves as a direct visual indicator of the magnitude and significance of each variable's impact on $T_{\max}$.

- Factors A (base fluid) and D (T_{inlet}): These parameters exhibit the most pronounced slopes across their respective levels. This provides clear visual evidence that the base fluid and T_{inlet} are the predominant factors governing the thermal management of the battery.
- Factor C (battery–battery distance): This variable also demonstrates a substantial downward trajectory, effectively reducing the temperature as the design transitions from Level 1 to Level 3, thereby confirming its importance in the cooling system's efficiency.
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): In stark contrast, the trend line associated with the nanoparticle volume fraction remains relatively flat. This nearly horizontal slope implies that altering the nanofluid concentration within the investigated 2% to 5% range exerts a marginal, if not negligible, statistical influence on the overall $T_{\max}$.

These graphical observations align with the quantitative hierarchy established by the 'Rank' metric (1-A, 2-D, 3-C, 4-B) derived from the preceding response tables (Tables 4 and 5).

To establish the optimal configuration among the four control variables, a main effects plot was generated utilizing the "smaller-the-better" S/N ratio data, as illustrated in Figure 4. On this chart, the vertical axis denotes the average S/N ratios. Within the framework of the Taguchi method, the maximum S/N ratio is the objective, as it indicates a system performance that closely meets the target (minimal $T_{\max}$) while maintaining robustness against external noise (minimal variance).

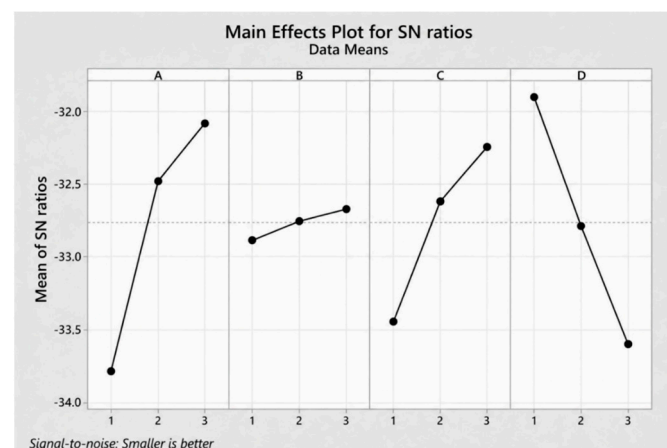


Figure 4. Main effects plot for (S/N) ratios of $T_{\max}$ ((A) base fluid; (B) $\Phi\text{-Al}_2\text{O}_3$; (C) battery–battery distance; (D) T_{inlet}).

An evaluation of the generated plot identifies the following levels as producing the highest S/N ratios for their respective factors:

- Factor A (base fluid): The peak S/N ratio occurs at Level 3 (Water).
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): The maximum S/N ratio is found at Level 3 (5%).
- Factor C (battery–battery distance): The highest S/N ratio is recorded at Level 3 ($3.5 \times r_{\text{batt}}$).
- Factor D (T_{inlet}): The peak S/N ratio is achieved at Level 1 (293.15 K).

This visual assessment serves to corroborate that the A3-B3-C3-D1 setup constitutes the optimal parametric combination for minimizing $T_{\max}$. This conclusion aligns seamlessly with the results derived from the main effects plot for means (Figure 3).

Moreover, the gradients of the plotted lines further validate the established hierarchy of factor significance. Factors A (base fluid) and D (T_{inlet}) exhibit the most acute variations

in S/N ratio across their levels, confirming their status as the predominant variables influencing thermal performance. In contrast, the nearly horizontal trajectory of the line representing Factor B ($\Phi\text{-Al}_2\text{O}_3$) indicates a minimal shift in the S/N ratio, substantiating its position as the least impactful parameter. These graphical observations are in complete accordance with the factor rankings previously delineated in the S/N response (Table 4).

ANOVA was executed to quantitatively evaluate the statistical significance and proportional impact of the four operational parameters (A, B, C, and D) on the battery $T_{\max}$. The outcomes of this ANOVA are detailed in Table 6.

Table 6. ANOVA for $T_{\max}$ means, The data marked with an asterisk in the table means Cannot be computed due to zero degrees of freedom for residual error (saturated design).

Source	DF	Seq SS	Adj SS	Adj MS	F	p
A	2	115.056	115.056	57.5278	*	*
B	2	1.056	1.056	0.5278	*	*
C	2	47.722	47.722	23.8611	*	*
D	2	92.056	92.056	46.0278	*	*
Residual Error	0	*	*	*		
Total	8	255.889				

Given the implementation of an L9 orthogonal array accommodating four factors across three distinct levels, all eight available degrees of freedom (DF) were entirely allocated to the main effects (Total DF = 9 experimental runs – 1 = 8; Factor DF = 4 factors $\times$ (3 levels – 1) = 8). This specific configuration constitutes a “saturated” design, thereby leaving zero DF assigned to residual error (DF_Error = 0). Consequently, traditional statistical metrics, namely F-values and p-values, cannot be computed, a limitation denoted by an asterisk (“*”) within the summary table.

Under these saturated conditions, the magnitude of each parameter’s influence on $T_{\max}$ is evaluated by analyzing the “adjusted sum of squares” (Adj SS) to derive its corresponding “percentage contribution” (P%). This percentage metric effectively quantifies the proportion of the total experimental variance that is attributable to each specific factor.

The analytical findings from the ANOVA provide robust statistical validation for the empirical trends previously observed in both the S/N ratio and main effects charts:

- Factor A (base fluid): Emerges as the most critical parameter governing $T_{\max}$, accounting for a dominant 44.96% of the overall variance.
- Factor D (T_{inlet}): Ranks as the second most influential variable, exhibiting a substantial percentage contribution of 36.00%.
- Factor C (battery–battery distance): Demonstrates a *moderate* impact on the thermal response, contributing 18.65% to the total variation.
- Factor B ($\Phi\text{-Al}_2\text{O}_3$): Yields a minimal contribution of merely 0.41%, indicating a *statistically insignificant (or negligible)* effect on $T_{\max}$.

Ultimately, this quantitative evaluation underscores that future optimization strategies aimed at mitigating battery temperature elevation should prioritize the careful selection and control of the base fluid and the coolant inlet temperature.

Both the Taguchi S/N ratio evaluation and the corresponding ANOVA results conclusively pinpointed the A3-B3-C3-D1 configuration as the ideal parametric setup for minimizing $T_{\max}$. In order to verify the thermal behavior of this optimal architecture comprising a water-based fluid, a 5% Al_2O_3 nanoparticle volume fraction, an inter-battery spacing of $3.5 \times r_{\text{batt}}$, and a coolant inlet temperature of 293.15 K and to rigorously

assess the efficacy of the optimization process, a subsequent confirmation simulation was executed utilizing COMSOL Multiphysics.

Figure 5 offers a comparative analysis between the outcomes of this confirmatory simulation (depicted as B) and the baseline, experimentally verified air-cooled reference model (depicted as A) that was established at the onset of the investigation.

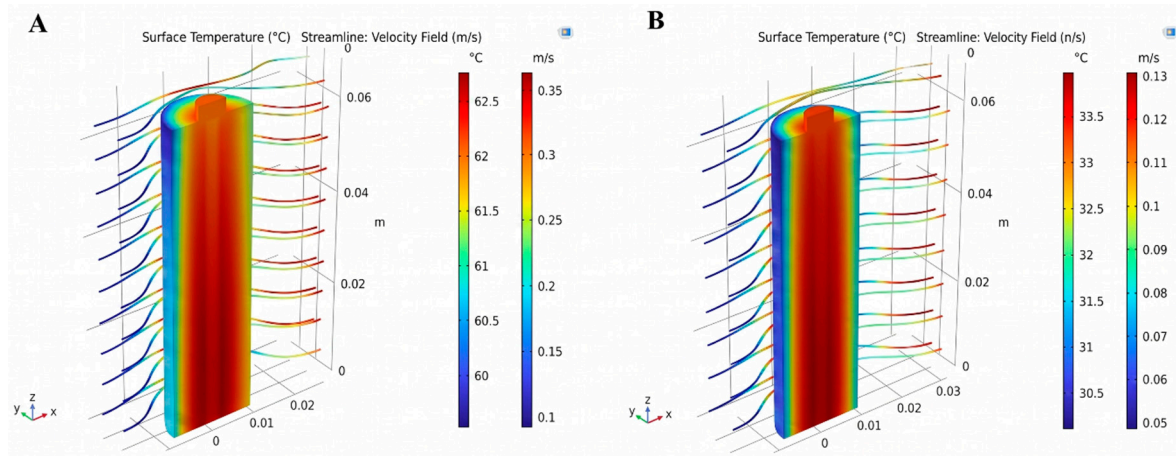


Figure 5. Comparison of surface temperature and velocity streamlines for the pre-optimization air-cooled model (A) and the Taguchi-Optimized (A3-B3-C3-D1) nanofluid-cooled model (B).

- Figure 5A (pre-optimization baseline): This panel illustrates the thermal profile of the initial air-cooled reference system. An inspection of the associated temperature contour scale (spanning 60 °C to 62.5 °C) reveals a predominantly red (elevated temperature) battery surface. Here, the $T_{\max}$ peaks at approximately 62.5 °C, a value that exceeds the conventional safe operating threshold for Li-ion cells (generally recognized as 60 °C), thereby introducing a substantial risk of thermal runaway.
- Figure 5B (post-optimization configuration): This panel displays the thermal distribution for the nanofluid-cooled system operating under the optimized A3-B3-C3-D1 parameters derived from the Taguchi methodology. The corresponding temperature scale (ranging from 30.5 °C to 33.5 °C), coupled with a predominantly blue (cooler) surface profile, signifies a profound enhancement in thermal management capabilities. Notably, the optimized architecture successfully constrains the $T_{\max}$ to a safe limit of approximately 33.5 °C.

This direct comparison provides compelling quantitative evidence of the Taguchi optimization's significant efficacy. Relative to the baseline air-cooled architecture, the optimized nanofluid cooling system yielded a reduction in battery $T_{\max}$ of 29.0 °C.

Crucially, the achieved $T_{\max}$ of 33.5 °C under the optimal conditions surpasses the lowest temperature recorded among the original L9 orthogonal array experiments (which was 35.5 °C during the L9 trial). This outcome definitively validates the robust predictive capacity of the Taguchi approach. It demonstrates that the methodology is not restricted to merely selecting the most favorable condition from a pre-defined experimental matrix; rather, it is highly capable of extrapolating a novel, mathematically derived optimal combination that yields demonstrably superior performance beyond the initially tested empirical boundaries.

Figure 6 illustrates the temperature change over an extended, cyclic operating period of 2100 s, encompassing both heating and cooling phases. This analysis is critical for evaluating the thermal stability and the risk of heat accumulation in the battery under real-world usage conditions.

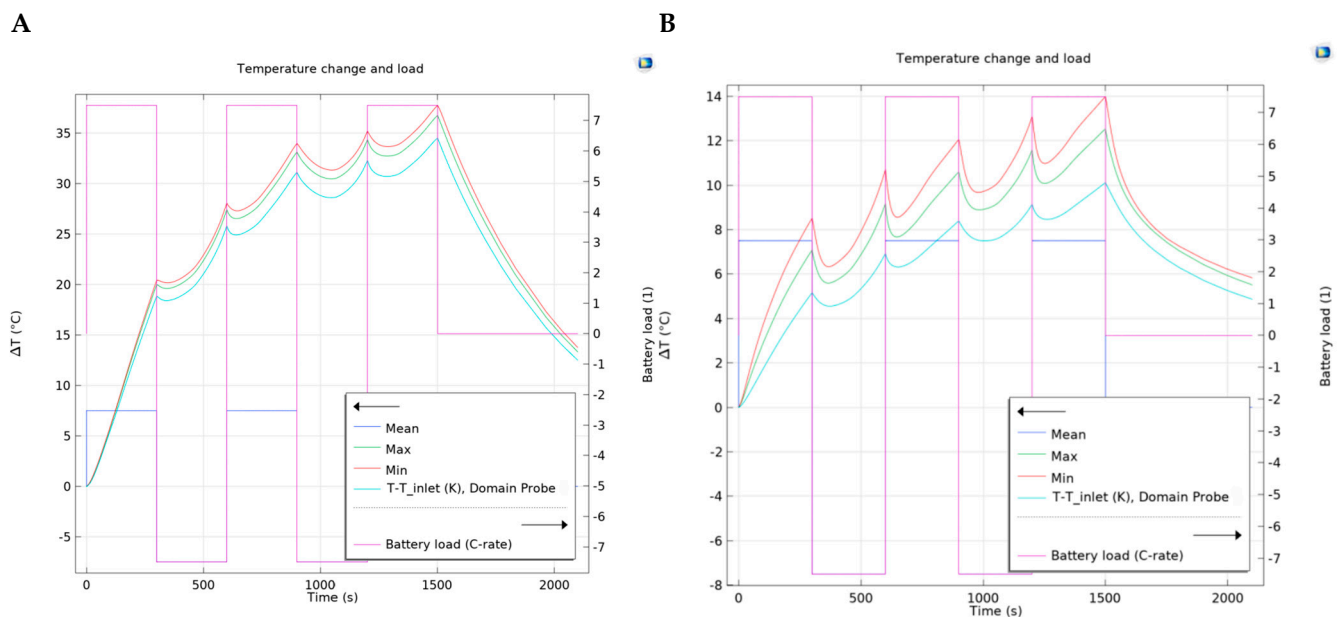


Figure 6. Comparison of ΔT over time for the pre-optimization ((A): air-cooled) and post-optimization ((B): A3-B3 C3-D1 nanofluid-cooled) models.

- Curve A (baseline air-cooled model): In the initial air-cooled reference model, the temperature rises rapidly during consecutive charge and discharge cycles, clearly demonstrating heat accumulation with a distinct ‘staircase’ effect. By the end of the 1500 s load period, the $T_{\max}$ rise (ΔT) reaches approximately 37 °C. This proves that air cooling is insufficient to keep the battery within safe operating limits under intensive cyclic loads.
- Curve B (optimized nanofluid model): The A3-B3-C3-D1 configuration, determined via the Taguchi method, records a dramatic improvement in thermal stability. Under the exact same severe cyclic load, the $T_{\max}$ rise at 1500 s is restricted to only 14 °C. The optimized system successfully reduces heat accumulation by approximately 62% compared with the air-cooled model. Furthermore, during the resting (cooling) phase after 1500 s, it is observed that the nanofluid cooling extracts heat from the system much faster, rapidly stabilizing the battery temperature.

These findings indicate that the cooling system driven by the dominant effects of the (A) base fluid (Water) and (D) T_{inlet} (293.15 K) not only reduces short-term peak temperatures but also maximizes battery life and safety by effectively preventing heat accumulation during long-term cyclic operations.

4. Conclusions

In this study, the Taguchi L9 orthogonal array methodology, combined with S/N ratio analysis and ANOVA, was successfully applied to minimize the $T_{\max}$ of a cylindrical Li-ion battery. Four 3-level control factors (base fluid, $\Phi\text{-Al}_2\text{O}_3$, battery–battery distance, and T_{inlet}) were investigated. The primary conclusions drawn from the results are summarized as follows:

1. Optimal parameters: Based on the “smaller-is-better” S/N ratio analysis, the optimal parameter combination to minimize $T_{\max}$ was determined to be A3-B3-C3-D1. This physically corresponds to a Water (W) base fluid, a 5% Al_2O_3 volume fraction, a $3.5 \times r_{\text{batt}}$ battery distance, and a 293.15 K (20 °C) T_{inlet} .
2. Factor influence (ANOVA): The ANOVA quantified the contribution of each factor to $T_{\max}$. The base fluid (Factor A) was identified as the most dominant factor, accounting

for 44.96% of the total variation. This was closely followed by the T_{inlet} (Factor D) with a 36.00% contribution. The battery–battery distance (Factor C) showed a moderate effect at 18.65%, while the $\Phi\text{-Al}_2\text{O}_3$ (Factor B) was found to be statistically insignificant within the range studied, contributing only 0.41%. This indicates that cooling performance is primarily dependent on the fluid’s thermal properties and its T_{inlet} .

3. Optimization confirmation: The confirmation simulation for the optimal A3-B3-C3-D1 configuration demonstrated the effectiveness of the optimization. The optimized nanofluid-cooled design achieved a T_{max} of 33.5 °C. This is 29.0 °C lower than the T_{max} of the initial, experimentally validated air-cooled reference model (62.5 °C).
4. Thermal stability and cyclic performance: The 2100 s cyclic analyses proved the superior thermal stability of the optimized design. The temperature rise, which reached 37 °C and showed a continuous upward trend at the end of 1500 s in the air-cooled model, was maintained at only 14 °C in the optimized nanofluid system. This result reveals that the system’s capacity to mitigate heat accumulation under heavy cyclic loads is more than 60% greater than that of the air-cooled baseline.
5. Method validation and reliability: The T_{max} of 33.5 °C achieved by the optimized design outperformed even the best result within the L9 experimental matrix (35.5 °C). This confirms that the Taguchi method not only selects the best among the tested combinations but also successfully predicts the true optimum point outside the initial experimental set. Additionally, the high efficiency of the system in both the heating and cooling phases demonstrates that the proposed BTMS design is highly reliable for practical, real-world applications.

In conclusion, the Taguchi method has been proven to be an efficient and powerful statistical tool for optimizing a BTMS.

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Data Availability Statement: The data presented in this study are available in the author’s completed PhD thesis [26]. Further details and datasets are available on request from the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

Li-ion	Lithium-ion
3D	Three-Dimensional
$\Phi\text{-Al}_2\text{O}_3$	Al_2O_3 Volume Fraction
T_{inlet}	Inlet Temperature
T_{max}	Maximum Temperature
S/N	Signal-to-Noise
ANOVA	Analysis of Variance
BTMS	Battery Thermal Management Systems
PCM	Phase Change Materials
EG	Ethylene Glycol

EO	Engine Oil
V_{inlet}	Inlet Velocity
DFN	Doyle–Fuller–Newman
P2D	Pseudo-2D
ΔT	Temperature Change
EGW	Ethylene Glycol–Water 30–70% vol.
DF	Degrees of Freedom
Adj SS	Adjusted Sum of Squares
P%	Percentage Contribution

Appendix A

The 1D electrochemical behavior of the Li-ion cell and the corresponding volumetric heat generation are resolved using the P2D DFN framework [27,28]. The governing equations applied in this study are summarized in Table A1.

Table A1. Governing equations for the DFN electrochemical and thermal model.

Physical Process	Governing Equation
Mass Conservation (Solid)	$\frac{\partial c_s}{\partial t} = \frac{D_s}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial c_s}{\partial r} \right)$
Mass Conservation (Liquid)	$\epsilon_e \frac{\partial c_e}{\partial t} = \nabla \cdot \left(D_{e,eff} \nabla c_e \right) + \frac{1-t_+}{F} j^{Li}$
Charge Conservation (Solid)	$\nabla \cdot \left(\sigma_{s,eff} \nabla \phi_s \right) - j^{Li} = 0$
Charge Conservation (Liquid)	$\nabla \cdot \left(\kappa_{e,eff} \nabla \phi_e \right) + \nabla \cdot \left(\kappa_{D,eff} \nabla \ln c_e \right) + j^{Li} = 0$
Electrochemical Kinetics	$j^{Li} = a_s i_0 \left[\exp \left(\frac{\alpha_a F}{RT} \eta \right) - \exp \left(-\frac{\alpha_c F}{RT} \eta \right) \right]$
Heat Generation	$Q = j^{Li} (\phi_s - \phi_e - U_{eq}) + j^{Li} T \frac{\partial U_{eq}}{\partial T} + Q_{ohm}$
Non-isothermal Feedback (Arrhenius)	$\Psi(T) = \Psi_{ref} \exp \left[\frac{E_a}{R} \left(\frac{1}{T_{ref}} - \frac{1}{T} \right) \right]$

Note: c_s and c_e are lithium concentrations; ϕ_s and ϕ_e are potentials; D_s and D_e are diffusion coefficients; j^{Li} is the transfer current density; η is the overpotential; Q is the total volumetric heat source. For the non-isothermal feedback loop, Ψ represents the temperature-dependent parameters (e.g., D_s , D_e , i_0), Ψ_{ref} is the reference value at T_{ref} , and E_a is the activation energy.

Table A2. Key geometric and electrochemical parameters for the 18,650 cell used in the DFN model [15].

Parameter	Negative Electrode	Separator	Positive Electrode
Thickness (μm)	55	30	60
Particle radius, r_p (μm)	2.5	-	0.5
Solid volume fraction, ϵ_s	0.384	-	0.60
Electrolyte volume fraction, ϵ_e	0.444	0.370	0.30
Initial solid concentration, $c_{s,0}$ (mol/m^3)	2205	-	20,944
Initial electrolyte concentration, $c_{e,0}$ (mol/m^3)	1200	1200	1200

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