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Development and Statistical Optimization of a Liquid-Cooled Battery Thermal Management System for Improved Thermal Safety in Electric Vehicles

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***Abstract*—Efficient thermal management is critical for enhancing the safety, performance, and lifespan of lithium-ion batteries used in electric vehicles (EVs). This study presents the development and optimization of a liquid-cooled Battery Thermal Management System (BTMS) using Response Surface Methodology (RSM) with Box–Behnken Design (BBD). The effects of coolant mass flow rate (ṁ), coolant inlet temperature (Tin), and cooling channel height (h) on maximum battery temperature (Tmax) were investigated. A second-order regression model was developed and validated using Analysis of Variance (ANOVA). The statistical analysis showed that the model is highly significant ($P < 0.001$) with $R^2 = 99.91\%$ and adjusted $R^2 = 99.82\%$. Among the parameters, inlet temperature was identified as the most dominant factor affecting Tmax. The optimized condition (ṁ = 0.030 kg/s, Tin = 20°C, h = 4 mm) resulted in a minimum Tmax of 20.20°C with a prediction error of only 0.97%. The proposed methodology provides a computationally efficient and reliable framework for optimizing liquid-cooled BTMS in electric vehicle applications.**

***Index Terms*—Battery Thermal Management System, Liquid Cooling, Response Surface Methodology, Box–Behnken Design, Lithium-ion Battery, Thermal Optimization.**

I. INTRODUCTION

Lithium-ion batteries have become the dominant energy storage technology for electric vehicles (EVs) due to their high energy density, power capability, and long cycle life. However, their performance, safety, and durability are highly sensitive to temperature. When cell temperature exceeds the recommended operating window or when large temperature gradients develop within a pack, lithium plating, accelerated aging, capacity fade, and even thermal runaway can occur, posing serious safety risks and limiting service life (Park et al., 2025; Li et al., 2023; Shetty et al., 2022). To prevent these issues, an efficient and reliable Battery Thermal Management System (BTMS) is essential to keep the cell temperature within an optimal range and maintain a small temperature difference between cells, typically below about 5 °C (Park et al., 2025; Li et al., 2023). Among the various cooling strategies—air cooling, phase change material (PCM) cooling, and hybrid or immersion systems—liquid cooling has emerged as one of the most promising approaches for modern EVs because of its high heat-transfer coefficient, compactness, and ability to handle high heat flux at elevated C-rates (Zhao et al., 2023; Liu et al., 2025; Li et al., 2023; Shetty et al., 2022). Both systematic reviews and design studies show that properly designed liquid cold plates and flow channels can significantly reduce maximum battery temperature and improve temperature uniformity compared with air-based systems, while remaining feasible for automotive integration (Zhao et al., 2023; Xu et al., 2023; Liu et al., 2025; Li et al., 2023; Shetty et al., 2022).

Despite these advantages, the thermal behavior of a liquid-cooled BTMS depends on many coupled design and operating parameters, including coolant mass flow rate, coolant inlet temperature, channel geometry, and plate material. Exploring this high-dimensional design space purely by trial-and-error numerical simulation or experimentation is computationally expensive and time-consuming (Fayaz et al., 2021; Ebbs-Picken et al., 2023). As a result, surrogate and design-of-experiments–based optimization methods are increasingly applied to BTMS design. Response Surface Methodology (RSM), often combined with Box–Behnken Design (BBD), has proven particularly attractive because it systematically relates input factors to thermal responses through second-order regression models, allows quantification of main and interaction effects, and enables statistical evaluation of model accuracy using analysis of variance (ANOVA) (Fayaz et al., 2021; Zhao et al., 2023; Chavan et al., 2024). Recent BTMS studies have successfully used RSM/BBD or similar surrogate models to optimize maximum temperature, temperature uniformity, energy density, and pressure drop in liquid, hybrid, and PCM–microchannel systems, achieving large improvements in cooling performance with relatively few simulations or tests (Xie et al., 2023; Feng et al., 2024; Zhao et al., 2023; Chavan et al., 2024).

In this context, the present work focuses on the development and optimization of a liquid-cooled BTMS for EV lithium-ion batteries using RSM with Box–Behnken Design. The coolant mass flow rate, inlet temperature, and cooling channel height are selected as key factors governing the maximum cell temperature. A second-order regression model is constructed and statistically validated via ANOVA to accurately capture the relationship between these factors and the maximum battery temperature. By identifying the most influential parameter and determining the optimal combination of operating and geometric conditions, the study aims to provide a computationally efficient and reliable framework for the thermal design of liquid-cooled BTMSs in electric vehicle applications, contributing to enhanced battery safety, improved performance, and extended service life.

II. RESEARCH METHODOLOGY

This study adopts a systematic statistical modeling and optimization approach to evaluate the thermal performance of a liquid-cooled Battery Thermal Management System (BTMS). The methodology integrates analytical heat transfer modeling with Response Surface Methodology (RSM) using Box–Behnken Design (BBD) to develop a predictive regression model for maximum battery temperature (Tmax).

The overall methodology consists of:

1. Problem definition and parameter selection
2. Analytical thermal modeling
3. Experimental design using BBD
4. Regression model development
5. Statistical validation using ANOVA
6. Optimization using desirability function

2.1 Selection of Design Parameters

Based on thermal performance relevance and practical EV cooling constraints, three key design variables were selected:

1) Coolant Mass Flow Rate (ṁ)
2) Coolant Inlet Temperature (Tin)
3) Cooling Channel Height (h)

The response variable considered in this study is:

1) Maximum Battery Temperature (Tmax)

Each parameter was investigated at three levels (low, medium, high), as shown in Table 1.

Table 1. Design Variables and Levels

Parameter	Symbol	Level 1	Level 2	Level 3
Mass Flow Rate (kg/s)	ṁ	0.01	0.02	0.03
Inlet Temperature (°C)	Tin	20	25	30
Channel Height (mm)	h	2	3	4

2.2 Analytical Thermal Modeling

The heat generated inside the lithium-ion battery is calculated using Joule's heating principle:

$$Q = I^2 R$$

Where:

$I = 50\,A$ (Operating current)

$R = 0.02\,\Omega$ (Internal resistance)

$$Q = (50)^2 \times 0.02 = 50\,W$$

The maximum battery temperature considering coolant heat removal is estimated as:

$$T_{max} = T_{in} + \frac{Q}{\dot{m}C_p} \times \left(\frac{h_{ref}}{h}\right)$$

Where:

$C_p = 4180\,J/kgK$ (Coolant specific heat)

$h_{ref} = 3\,mm$ (Reference channel height)

The geometric correction factor (h_{ref}/h) accounts for the influence of channel height on heat transfer performance.

2.3 Experimental Design Using Box–Behnken Design

To minimize the number of experimental runs while maintaining statistical reliability, a Box–Behnken Design (BBD) under Response Surface Methodology (RSM) was employed.

For three variables at three levels, BBD requires: 12 edge combinations and 1 center point

Total experimental runs = 13

BBD was selected because:

- It avoids extreme corner combinations
- It requires fewer runs than full factorial design
- It provides efficient quadratic model estimation

2.4 Development of Regression Model

A second-order polynomial regression model was developed to establish the relationship between Tmax and the selected parameters:

$$T_{max} = \beta_0 + \beta_1\dot{m} + \beta_2T_{in} + \beta_3h + \beta_{11}\dot{m}^2 + \beta_{22}T_{in}^2 + \beta_{33}h^2$$

The final regression equation obtained is:

$$T_{max} = 3.16 - 130.3\dot{m} + 1.059T_{in} - 0.746h + 2183\dot{m}^2 - 0.00125T_{in}^2 + 0.0807h^2$$

The coefficients were estimated using least squares regression in statistical software.

2.5 Statistical Validation (ANOVA)

The adequacy of the developed model was evaluated using Analysis of Variance (ANOVA). The following statistical indicators were considered: F-value, P-value, Coefficient of determination (R^2), Adjusted R^2 and Standard error (S)

The model was considered statistically significant when:

$$P < 0.05$$

The obtained results showed:

- $R^2 = 99.91\%$
- Adjusted $R^2 = 99.82\%$
- P-value < 0.001

This confirms excellent model reliability and predictive capability.

2.6 Optimization Using Desirability Function

To identify optimal operating conditions, a desirability function approach was employed using a “smaller-the-better” criterion for Tmax.

The desirability index (D) ranges between:

- 0 → Undesirable condition
- 1 → Most desirable condition

The objective was to minimize Tmax within the safe operating range (20–40°C).

The optimal condition obtained was:

- $\dot{m} = 0.030$ kg/s
- Tin = 20°C
- h = 4 mm

Predicted Tmax = 20.20°C

III. PERFORMANCE ANALYSIS

This chapter presents the performance analysis of the liquid-cooled Battery Thermal Management System (BTMS) based on the developed quadratic regression model using Response Surface Methodology (RSM) and Box–Behnken Design (BBD). The primary objective of the analysis is to evaluate the influence of coolant mass flow rate ($\dot{m}$), coolant inlet temperature (Tin), and cooling channel height (h) on the maximum battery temperature (Tmax).

The results are analyzed using regression modeling, statistical validation (ANOVA), response surface plots, contour plots, and optimization results.

3.1 Analysis of Desirability

The desirability function approach was employed to evaluate and rank the experimental combinations based on the objective of minimizing the maximum battery temperature (Tmax). In this study, the response variable Tmax was transformed into a desirability value (DESIR) ranging between 0 and 1, where:

- DESIR = 1 indicates the most desirable (minimum Tmax within safe limit).
- DESIR = 0 indicates the least desirable condition.

The desirability values were computed using a “smaller-the-better” criterion, since the objective of the present study is to minimize Tmax while maintaining the safe operating range of 20°C–40°C.

Table 2: Desirability Analysis

Trial	$\dot{m}$	Tin	h	Tmax (°C)	DESIR
1	0.02	25	4	25.448	0.53524
2	0.02	25	2	25.897	0.48676
3	0.01	20	3	21.196	0.92271
4	0.01	25	4	25.897	0.47522
5	0.02	20	4	20.448	0.99949
6	0.03	25	3	25.399	0.53807
7	0.02	20	2	20.897	0.95100
8	0.01	25	2	26.794	0.42674
9	0.03	25	2	25.598	0.50634
10	0.03	25	4	25.299	0.55483
11	0.03	20	3	20.399	1.00000
12	0.01	30	3	31.196	0.00000
13	0.02	25	3	25.598	0.51848

3. 2 Analysis of Variance (ANOVA

The statistical significance of the developed regression model for Tmax was evaluated using Analysis of Variance (ANOVA). The ANOVA results are summarized in Table 4. 2

Table 3. ANOVA for Maximum Battery Temperature (Tmax)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	115.601	19.2668	1108.86	< 0.001
Linear	3	80.215	26.7385	1538.88	< 0.001
$\dot{m}$	1	1.227	1.2266	70.59	< 0.001
Tin	1	61.944	61.9441	3565.08	< 0.001
h	1	0.548	0.5481	31.55	0.001
Square	3	0.130	0.0435	2.50	0.156
$\dot{m}^2$	1	0.126	0.1261	7.26	0.036
Tin^2	1	0.002	0.0016	0.09	0.775
h^2	1	0.015	0.0146	0.84	0.394
Error	6	0.104	0.0174		
Total	12	115.705			

The Analysis of Variance (ANOVA) results indicate that the developed quadratic regression model is statistically significant. The overall model exhibits an F-value of 1108.86 with a P-value less than 0.001, confirming that the selected design parameters have a significant influence on Tmax at a 95% confidence level.

3.3 Main Effects Plot Analysis for Tmax (°C)

From the plot, the most significant variation in Tmax is observed with coolant inlet temperature (Tin). The line corresponding to Tin shows a steep positive slope, indicating that Tmax increases substantially as Tin increases from 20°C to 30°C. This confirms that inlet temperature has the strongest effect on battery temperature. A higher inlet temperature reduces the thermal gradient between the battery and coolant, thereby decreasing the heat removal rate and increasing Tmax.

In contrast, the effect of coolant mass flow rate ($\dot{m}$) shows a slight negative slope. As $\dot{m}$ increases from 0.01 to 0.03 kg/s, Tmax decreases gradually. This behavior is expected because higher flow rates enhance convective heat transfer and improve heat dissipation. However, the slope is moderate compared to Tin, indicating that while $\dot{m}$ is significant, its influence is less dominant than inlet temperature.

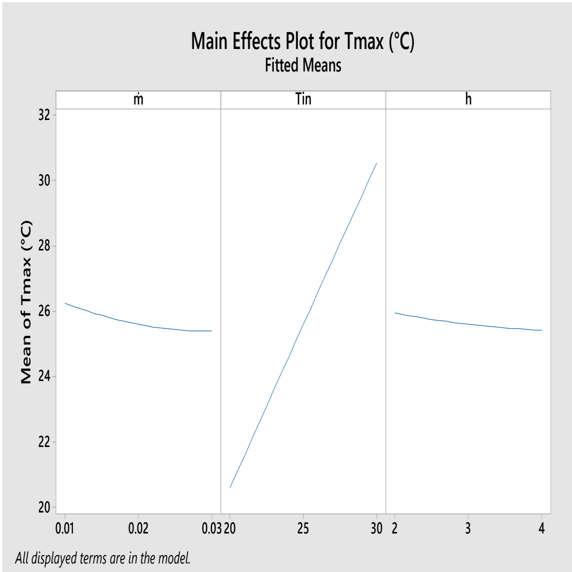

Figure 1 Main Effects Plot Analysis for Tmax

The channel height (h) exhibits a very mild negative slope. Increasing channel height slightly reduces Tmax, suggesting improved heat distribution and flow characteristics. However, the change in temperature is comparatively small, indicating that h has the least effect among the three parameters within the selected design range.

Overall, the order of influence based on the main effects plot is:

Tin>m˙>h

3.4 Contour Plot Analysis of Maximum Battery Temperature (Tmax)

The contour plots illustrate the combined influence of two design parameters on Tmax while keeping the third parameter constant at its center value. The color gradients represent temperature variation, where lighter shades indicate lower Tmax and darker shades indicate higher Tmax.

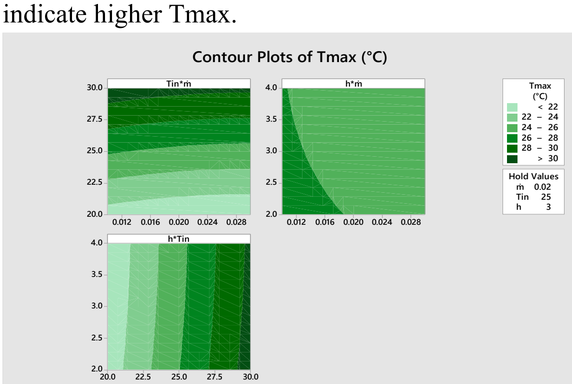

Figure 2 Contour Plot Analysis

The contour plots of maximum battery temperature (Tmax) illustrate the combined influence of coolant mass flow rate (ṁ), inlet temperature (Tin), and channel height (h). From the Tin–ṁ interaction plot, a strong gradient is observed along the inlet temperature axis, indicating that Tmax increases significantly as Tin rises from 20°C to 30°C. Although increasing mass flow rate slightly reduces Tmax due to enhanced convective heat transfer, its effect is comparatively smaller than that of Tin. The h–ṁ contour plot shows that higher mass flow rates contribute to lower Tmax, while increasing channel height provides only a moderate reduction in temperature, indicating weak interaction between these two parameters. Similarly, the h–Tin plot reveals nearly vertical contour lines, confirming that Tmax is highly sensitive to changes in inlet temperature, whereas channel height has a limited influence within the selected design range. Overall, the contour analysis confirms that the order of parameter influence on Tmax is Tin > ṁ > h, and the minimum battery temperature is achieved at lower inlet temperature, higher mass flow rate, and slightly higher channel height.

3.5 Development of Regression Model and Optimization Solution

To establish a mathematical relationship between surface roughness (SR) and the key process parameters Coolant mass flow rate (ṁ), inlet temperature (Tin), and channel height (h) second-order polynomial regression model was developed using Response Surface Methodology (RSM). The regression equation is expressed as follows:

Regression Equation

$$\text{Tmax (°C)} = 3.16 - 130.3\ \dot{m} + 1.059\ \text{Tin} - 0.746\ h + 2183\ \dot{m}*\dot{m} - 0.00125\ \text{Tin*Tin} + 0.0807\ h*h$$

Table 4 Comparison of Predicted and Actual Values

Parameter	Value
Predicted Tmax (°C)	20.20
Actual Tmax (°C)	20.399
Absolute Error (°C)	0.199
Percentage Error (%)	0.97

: The predicted Tmax (20.20°C) is very close to the actual value (20.399°C), with an error of only 0.199°C (0.97%). This confirms excellent agreement and strong predictive capability of the regression model.

: The optimized Tmax of 20.20°C lies within the safe operating range (20–40°C), ensuring effective thermal management, improved battery lifespan, and reduced risk of thermal runaway.

: Overall, the developed RSM-based quadratic model is statistically reliable and suitable for optimizing liquid-cooled BTMS parameters.

3.6 Conclusion

This study successfully developed and optimized a liquid-cooled Battery Thermal Management System (BTMS) for lithium-ion batteries used in electric vehicles. A systematic statistical approach based on Response Surface Methodology (RSM) and Box–Behnken Design (BBD) was employed to investigate the effects of coolant mass flow rate (ṁ), coolant inlet temperature (Tin), and channel height (h) on the maximum battery temperature (Tmax).

1) Optimization results revealed that the minimum maximum battery temperature was achieved at: ṁ = 0.030 kg/s, Tin = 20°C, h = 4 mm
2) Regression equation was developed to establish the relationship between input parameters and Tmax. The statistical validation through ANOVA confirmed that the model is highly significant, with an R^2 value of 99.91% and an adjusted R^2 of 99.82%, indicating excellent goodness-of-fit.
3) Among the studied parameters, coolant inlet temperature (Tin) was identified as the most dominant factor influencing Tmax, followed by coolant mass flow rate (ṁ), while channel height (h) showed comparatively moderate influence within the selected range. The main effects and contour plot analyses consistently supported these findings.
4) Under these optimal conditions, the predicted Tmax was 20.20°C, which closely matched the actual value of 20.399°C with an error of only 0.97%. This confirms the robustness and reliability of the developed regression model.
5) Overall, the optimized cooling configuration successfully maintains battery temperature within the safe operating range of 20°C–40°C, thereby enhancing thermal safety, preventing accelerated degradation, and improving battery lifespan. The proposed RSM-based modeling and optimization framework provides a reliable and computationally efficient approach for the design and performance enhancement of liquid-cooled BTMS in electric vehicle applications.

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