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A NUMERICAL INVESTIGATION ON THERMAL MANAGEMENT SYSTEM DESIGN FOR 4680 CYLINDRICAL LITHIUM-ION BATTERIES

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1. ABSTRACT

This study proposes a battery thermal management system (BTMS) for the 4680 battery module using a double-layer cold plate design, with aerogel utilized as a heat insulation material between the cells. A 2-dimensional finite element model is established to simulate both the thermal behaviour of battery cells and the heat transfer and hydrodynamic characteristics within the system. The design parameters of this proposed cooling strategy were globally optimized using the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, coupled with a surrogate back propagation (BP) neural network model to reduce computational cost.

2. INTRODUCTION

The demand for higher energy density in battery storage systems is growing across transportation and energy storage sectors. Large-format battery cells can minimize the control circuits within the battery system, thereby enhancing both the reliability and the volumetric energy density of the battery pack. However, the larger cell volume may form a larger thermal gradient inside the battery, which poses a major challenge to the detection technology and thermal management design [1].

The design of the battery thermal management system needs to consider both extending battery life and ensuring safety under abuse conditions. Thermal insulation materials have low thermal conductivity, which may reduce the cooling efficiency of battery modules/batteries under normal operating conditions. Consequently, when employing heat insulation materials, it is essential for the battery module/pack to incorporate well-designed thermal pathways to facilitate heat dissipation. The heat dissipation rate of a cell is strongly affected by its surface-to-volume ratio and thermal conductivity. The thermal conductivity of the battery jelly roll is notably elevated in the axial direction. The evaluation of the heat dissipation performance of 4680 tabless cells indicated that basic cooling could potentially offer greater efficiency [2].

3. METHODOLOGY

The Bernardi equation is employed to calculate the thermal generation rate of the battery. The internal resistance of the 4680 battery is calculated using the value from the literature [2], which is based on a reconstructed model of the 21700 M50T. The active materials and electrolyte properties of the battery are assumed to be consistent with the 21700 M50T. Additionally, the entropy temperature coefficient (dU /dT) of the battery is determined by its chemical properties rather than its geometric configuration. Therefore, the

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entropy temperature coefficient of 21700 M50T measured in the previous work is applied in this study [3]. The battery cell is regarded as an anisotropic heat transfer and stable heat source. The material of the top cover and safety devices is assumed to be the same as the steel can. A top/based double-layer cold plate configuration with antiparallel flow directions is used to alleviate the temperature gradient within the battery module induced by the directional flow of the inlet. Fig.1 demonstrates the BTMS employing a double-layer cold plate configuration, wherein aerogel acts as a thermal insulation agent interspersed among the cells.

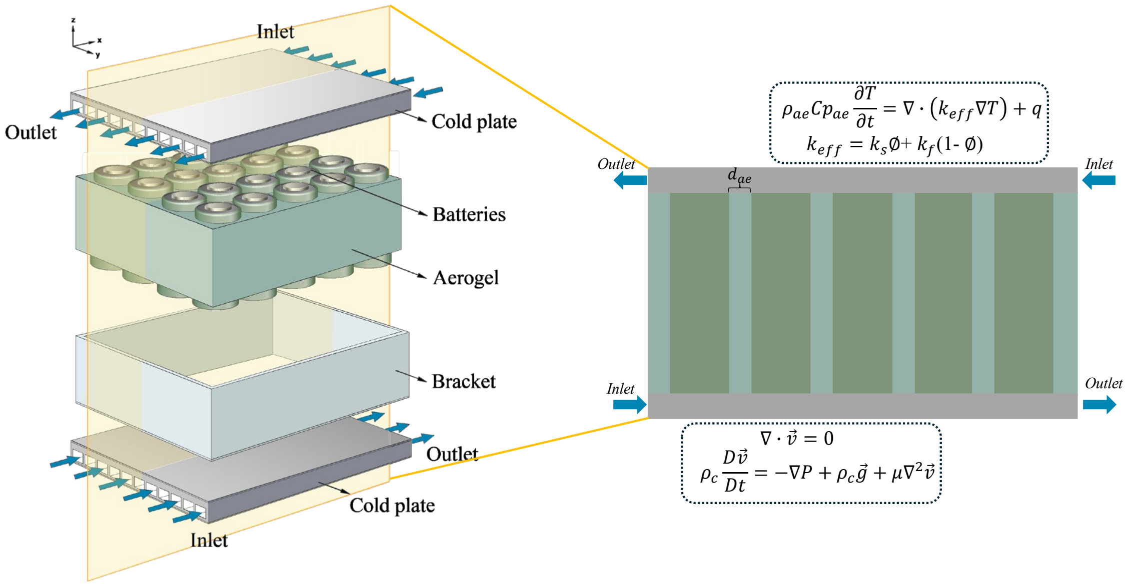

Fig. 1 Schematic diagram of the BTMS

The simulation results data of the FE model were used to train the BP neural network. The trained BP neural network is used to accelerate the multi-objective optimization process. MOPSO is used to establish the Pareto front for storing alternative solutions, which is easier to implement and converges faster than other optimization algorithms in the case of fewer optimization objectives [4]. The multi-objective optimization of BTMS focuses on two main goals: minimizing temperature gradient and temperature rise of the battery module. Design parameters include the inlet velocity of coolant (V_{inlet}), thickness (d_{ae}), specific heat capacity (Cp_{ae}), and thermal conductivity (k_{ae}) of aerogel. The values for these design parameters are confined to specific ranges.

4. RESULTS

In the case study, the battery cells performed a constant current discharge ranging from 1C to 3C, with the depth of discharge (DOD) maintained at 60 %. Sensitivity analyses are commonly used to evaluate how design parameters influence objectives. Fig. 2 (a) demonstrates the impact of aerogel thickness and coolant inlet velocity on maximum temperature during the 3C discharging rate. On the other hand, Increasing the inlet flow rate notably reduces the temperature rise in cells, but enlarges the temperature gradient within the battery module. Fig. 2 (b) illustrates the trade-off between temperature rise and temperature uniformity by the Pareto frontier curve, with the ideal vectors (P_{ideal}) and nadir vectors (P_{nadir}) defining the respective lower and upper limits of the solution space.

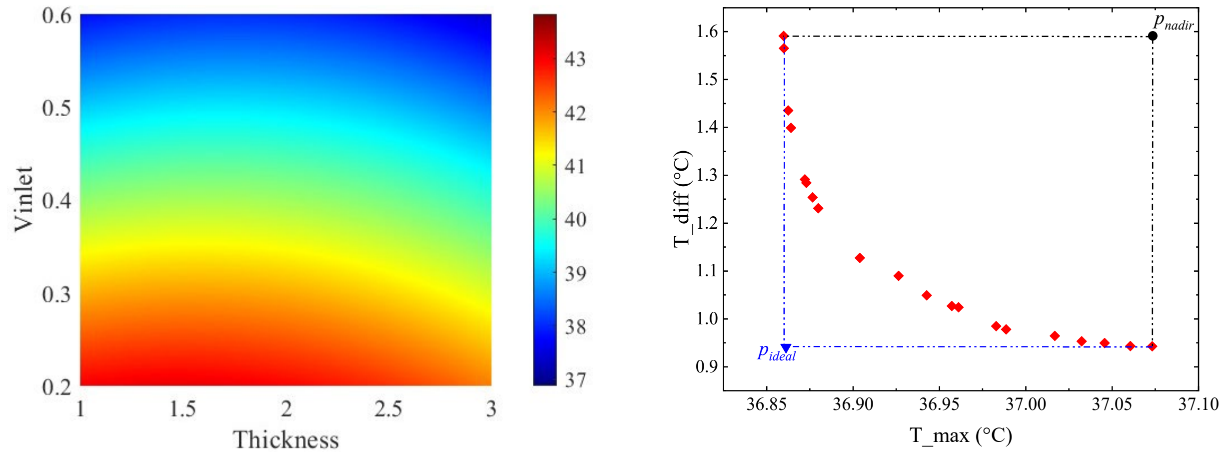

Fig. 2 Schematic diagram of simulation results: (a) sensitivity of maximum temperature of cells to V_{inlet} and d_{ae}; (b) Pareto frontier curve

5. CONCLUSIONS

In this study, a thermal management strategy is proposed for large 4680 batteries, incorporating double-layer cold plates and aerogel insulation materials. A sensitivity analysis quantified the effect of cold plate flow rate, aerogel thickness, and thermophysical parameters on the temperature consistency and rise in battery modules. The proposed thermal management solution employs a machine learning-assisted computational framework for multi-objective optimization. The Pareto frontier reveals multiple non-unique solutions to the design problem, enabling designers to initially identify all viable solutions that meet the objective function, and subsequently refine their choices based on design constraints.

REFERENCES

[1] A. Fordham *et al.*, “Correlative non-destructive techniques to investigate aging and orientation effects in automotive Li-ion pouch cells,” *Joule*, vol. 7, no. 11, pp. 2622–2652, 2023, doi: https://doi.org/10.1016/j.joule.2023.10.011.

[2] S. Li *et al.*, “How to enable large format 4680 cylindrical lithium-ion batteries,” *Appl. Energy*, vol. 349, p. 121548, 2023, doi: https://doi.org/10.1016/j.apenergy.2023.121548.

[3] Z. Sun *et al.*, “Algorithm-driven optimization of lithium-ion battery thermal modeling,” *J. Energy Storage*, vol. 65, p. 107388, 2023, doi: https://doi.org/10.1016/j.est.2023.107388.

[4] Y. Cui *et al.*, “Review: Multi-objective optimization methods and application in energy saving,” *Energy*, vol. 125, pp. 681–704, 2017, doi: https://doi.org/10.1016/j.energy.2017.02.174.