

Thermal management of battery energy storage systems: Challenges and AI-assisted solutions

Haoran Liu,¹ Hewu Wang,¹ Ruzhu Wang,^{2,*} and Minggao Ouyang^{1,*}

¹School of Vehicle and Mobility, Tsinghua University, Beijing, 100084, China

²Institute of Refrigeration and Cryogenics, Shanghai Jiao Tong University, Shanghai, 200240, China

*Correspondence: rzwang@sjtu.edu.cn (R. W.); ouymg@mail.tsinghua.edu.cn (M. O.)

Received: October 11, 2025; Accepted: January 13, 2026; Published Online: January 16, 2026; <https://doi.org/10.59717/j.xinn-energy.2026.100141>

© 2026 The Author(s). This is an open access article under the CC BY license (<https://creativecommons.org/licenses/by/4.0/>).

Citation: Liu H., Wang H., Wang R., et al. (2026). Thermal management of battery energy storage systems: Challenges and AI-assisted solutions. *The Innovation Energy* 3:100141.

Battery energy storage systems (BESS) are a cornerstone of net-zero energy systems, yet their safety, performance, and lifetime are fundamentally constrained by thermal management. Existing approaches primarily focus on internal cooling strategies such as air, liquid, and immersion cooling, while the thermal interactions between BESS and the broader energy system remain insufficiently explored. Here, we classify current thermal management technologies and discuss the emerging role of artificial intelligence in simulation, optimization, sensing, and control. We further argue that the substantial waste heat generated by large-scale BESS represents an underutilized energy resource. Integrating intelligent thermal management with waste heat recovery offers pathways toward safer, more efficient, and more sustainable deployment of BESS in future energy systems.

THERMAL MANAGEMENT

BESS are expected to play a dominant role among future energy storage technologies owing to their high operational flexibility and strong geographic adaptability. Batteries are highly sensitive to operating temperature. For commonly used lithium-ion batteries (LIBs), temperatures between 0 °C and 40 °C are generally acceptable, while a narrower range of 15–35 °C is preferred, with temperature uniformity maintained within 5 °C. Operating outside this range may adversely affect battery lifespan, efficiency, and thermal safety. During the operation, a portion of the input energy is inevitably converted into heat. The energy efficiency of LIBs typically ranges from 85% to 95%. For a 1 MWh battery energy storage system, assuming 5% of the input energy is dissipated as heat, charging and discharging generate approximately 10–50 kW of thermal power, underscoring the need for dedicated thermal management systems (TMS).

The TMS of BESS must fulfill multiple functions, including cooling, pre-heating, temperature homogenization, and the suppression of heat propagation during thermal runaway events. TMS consists of two interacting parts: the internal thermal organization surrounding the batteries and the external heating and cooling sources (Figure 1). The internal component focuses on creating efficient thermal pathways to facilitate heat transfer between the batteries and carriers, while the external sources aim to reduce energy consumption and enhance system reliability.

INTERNAL ORGANIZATION

Heat transfer fundamentally occurs via conduction, convection, and radiation, with convection typically dominating the overall heat transfer within BESS. Common convective thermal carriers include air, single-phase liquids, and two-phase refrigerants, whose heat transfer coefficients increase in that order due to their intrinsic properties. Thermal carrier selection is governed by physical properties such as thermal conductivity, heat capacity, viscosity, electrical conductivity, dielectric constant, flammability, material compatibility, and cost, which collectively determine system efficiency, safety, and reliability. The organization of the thermal carrier further determines the thermal management strategy. Direct contact with the battery, either air or liquid, corresponds to air and immersion cooling, respectively, while separation by a cold plate with single-phase liquids or two-phase refrigerants corresponds to liquid and direct cooling.¹ Among these approaches, immersion cooling is emerging as a promising solution for large-capacity BESS, providing excellent temperature uniformity while inherently reducing the risks of thermal runaway and fire.

Besides, several promising technologies are also under exploration, including phase-change materials (PCMs), heat pipes, internal-current heating, and

advanced thermal conduction or insulation materials.¹ A key thermal characteristic of BESS is that battery heat flux is moderate due to relatively low charging and discharging rates, while requirements for temperature uniformity and safety remain high. Transient thermal behavior from dynamic charging and discharging necessitates a rapid response from TMS. Consequently, a primary challenge for BESS is to temporally and spatially adjust thermal pathways to maintain uniform temperature. For example, in typical cubic battery packs, internal cells naturally exhibit higher thermal resistance than external ones, which can be compensated by adjusting thermal conductivity or coolant flow. Furthermore, the performance of technologies such as immersion cooling and PCMs depends strongly on material properties, highlighting the critical role of material innovation. These considerations underscore the importance of co-design across materials, devices, and systems, with appropriate placement of multiple technologies to achieve efficient BESS thermal management.

HEATING AND COOLING SOURCE

Internal thermal organization technologies primarily facilitate the transfer of heat generated by batteries to an appropriate thermal carrier, whereas external heating and cooling sources must be integrated and coordinated to ensure the continuous and reliable operation of the TMS. Conventional research on battery TMS has primarily focused on internal thermal organization. However, given the relatively moderate heat flux of batteries (10²–10³ W/m²) compared with other electronic devices (up to 10⁷ W/m²), the primary bottleneck of TMS may not lie in internal heat transfer. Instead, the design of external heating and cooling sources is likely to dominate the overall energy efficiency of the TMS, yet this aspect remains insufficiently explored.

The source component connects the internal thermal organization to the ambient environment, with its operation influenced by ambient parameters. For the most common operating parameter, ambient temperature, BESS cooling and heating are driven by temperature differences and achieved using fans, chillers, and heat pumps. A typical chiller has a COP of approximately 4, meaning 1 unit of electricity generates 4 units of cooling power. Besides, humidity can be used for cooling via technologies such as cooling towers and evaporative cooling. Evaporative cooling can reach a COP of up to 30 under certain water consumption, with performance highest in low-humidity environments. Furthermore, the TMS source can benefit from thermal radiation, such as solar thermal pre-heating and sky radiative cooling, without additional energy consumption.²

Beyond the thermal management of the batteries themselves, the waste heat generated by BESS can play a significant role in integrated energy systems through interactions with buildings and industrial processes. For example, coupling a BESS with buildings not only facilitates a zero-carbon electricity microgrid but also enables an interactive TMS. The overall energy efficiency of such a combined TMS is further enhanced by scale effects: as the scale of the refrigeration system increases, the COP of chillers improves, making the integrated BESS-building system more efficient than a single-container BESS. During the heating season, waste heat from BESS can be utilized for district space heating. With temperature upgrading via heat pumps, the 10–50 kW of heat generated by a hypothetical 1 MWh BESS could potentially meet the space-heating demand of buildings ranging from 300–1,500 m². Waste heat, with temperature upgrading via heat pumps, can also be integrated into various industrial processes, including thermoelectric generation, thermally driven cooling, water purification, atmospheric water

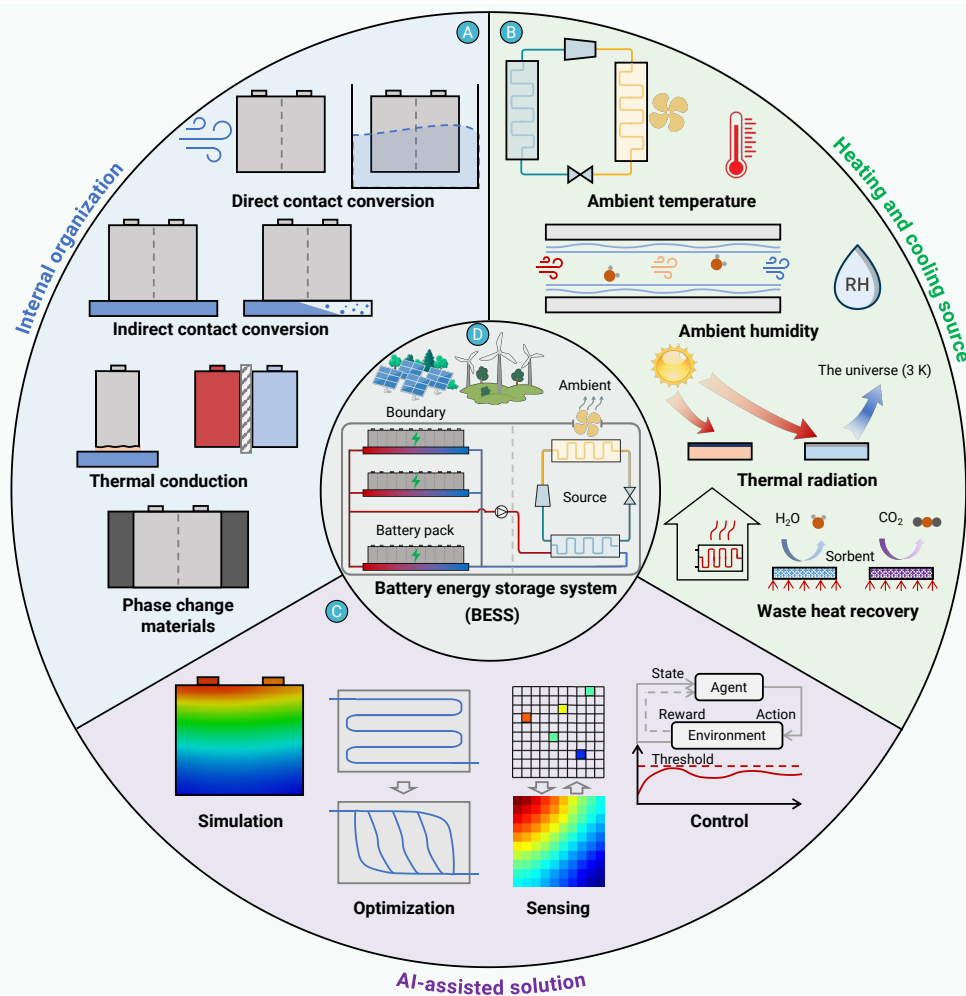


Figure 1. Schematic of the TMS for BESS (A) Internal thermal organization. (B) Heating and cooling sources. (C) AI-assisted solutions. (D) BESS system.

BESS is maintaining temperature uniformity, which requires accurate knowledge of spatial temperature distributions. Conventional strategies rely on in-situ temperature sensors, yet the optimal number and placement of these sensors remain largely unresolved. AI approaches, such as neural network-based strategies, offer a promising pathway for optimizing sensor deployment and reconstructing full temperature fields from limited measurements, thereby enabling accurate real-time thermal monitoring.⁵ Furthermore, during TMS operation, control actions must be coordinated across multiple components, including fans, pumps, compressors, and valves. Leveraging the aforementioned thermal model as a surrogate, reinforcement learning and other AI algorithms can derive optimal control policies, enabling adaptive and energy-efficient thermal management under dynamic operating conditions.

In summary, effective thermal management is essential for the safe and efficient operation of BESS, and AI algorithms can enhance TMS through both offline thermal design and real-time sensing and control. Beyond conventional investigations within the battery pack, thermally integrating BESS with surrounding multi-energy systems will become increasingly important for achieving a sustainable future.

harvesting, and carbon capture.³ Consequently, analyzing the feasibility, revenue, thermodynamic performance, and emissions of these BESS-applied technologies is essential to optimize system performance and benefits.

AI-ASSISTED SOLUTION

Effective TMS design for BESS requires both hardware technologies and intelligent algorithms, with AI supporting thermal simulation, structural optimization, real-time thermal sensing, and system control. Thermal simulation of BESS spans multiple scales, from the cell level (cm) to the pack level (m) and up to container systems (10 m), governed by partial differential equations (PDEs) describing heat transfer and fluid dynamics. Direct numerical solutions of these full-field equations are computationally intensive, so conventional approaches typically rely on multi-scale simulations, where sub-level components are solved sequentially and coupled via boundary conditions. Emerging AI techniques can accelerate this process by learning coarse-grained PDE approximations, constructing reduced-order ordinary differential equation models, and representing solution operators to enhance traditional numerical algorithms, using approaches such as physics-informed neural networks and recurrent sequence models.⁴ Based on thermal models, the structure and geometry of surrounding heat sinks and cold plates can be optimized to balance thermal resistance and carrier distribution and maintain temperature uniformity, with neural operator-based and surrogate learning optimization algorithms accelerating the solution process.

Beyond offline thermal design, AI algorithms can also enhance the real-time sensing and control of TMS, enabling optimal performance under transient workloads and varying ambient conditions. A key challenge for TMS in

REFERENCES

1. Rao Z., Lyu P., Li M., et al. (2025). A thermal perspective on battery safety. *Nat. Rev. Clean Tech.* 1:511–524. DOI:10.1038/s44359-025-00073-x
2. Fei J., Zhang X., Han D., et al. (2025). Passive cooling paint enabled by rational design of thermal-optical and mass transfer properties. *Science* 388:1044–1049. DOI:10.1126/science.adt3372
3. Diaz-Marín C. D. and Berquist Z. J. (2025). Flipping the switch: carbon-negative and water-positive data centers through waste heat utilization. *Energy Environ. Sci.* 18:8403–8413. DOI:10.1039/d5ee02676h
4. Brunton S. L. and Kutz J. N. (2024). Promising directions of machine learning for partial differential equations. *Nat. Comp. Sci.* 4:483–494. DOI:10.1038/s43588-024-00643-2
5. Liu X., Peng W., Zhang X., et al. (2025). Enhancing deep learning-based field reconstruction with a differentiable learning framework. *Nat. Machine Intel.* 7:1129–1140. DOI:10.1038/s42256-025-01063-1

FUNDING AND ACKNOWLEDGMENTS

This research was supported by the National Natural Science Foundation of China (Grant No. 52293411, 52036004), and the National Key Research and Development Program of China (Grant No. 2024YFE0213000).

AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.