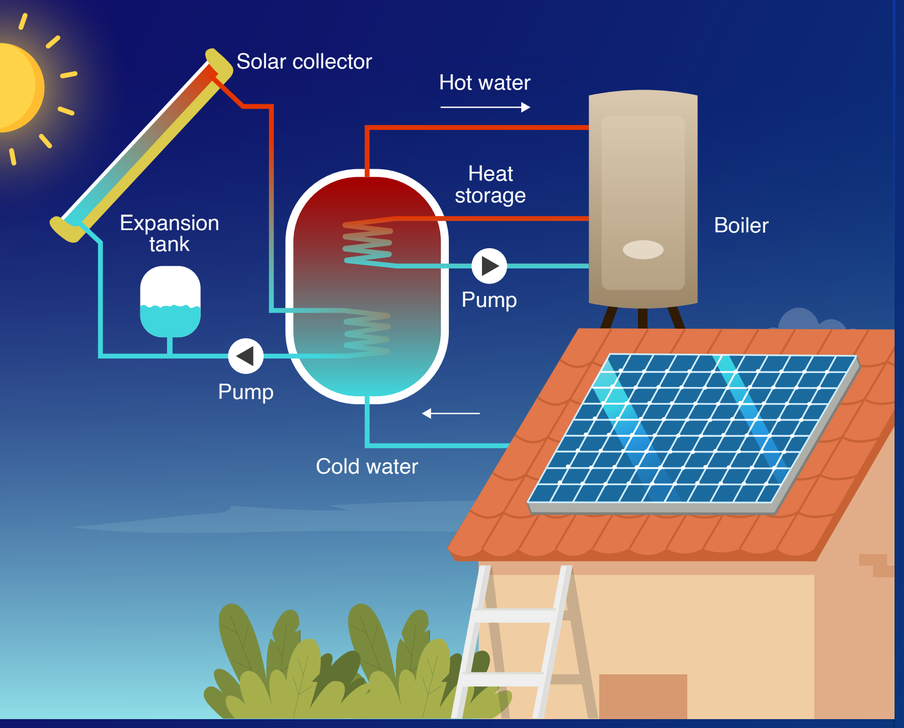
A physics-informed AI framework for latent heat thermal energy storage (LHTES) system optimization

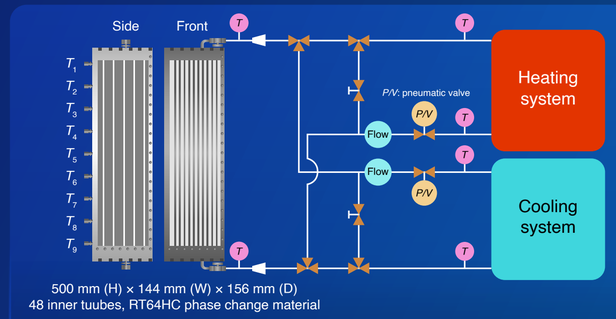
LHTES systems offer substantial efficiency benefits by utilizing phase change materials





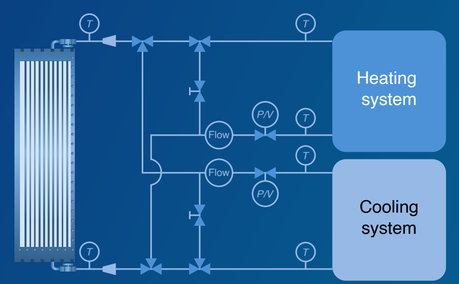
However, the design of LHTES systems is computationally expensive due to slow computational fluid dynamics (CFD) simulations

Physics-informed neural networks (PINNs) for design optimization of LHTES



500 mm (H) × 144 mm (W) × 156 mm (D)
48 inner tuubes, RT64HC phase change material

Experimentally validated LHTES system
CFD model



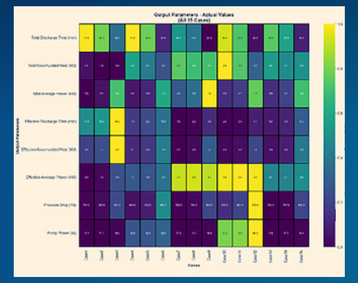
High-fidelity digital twin

Ground truth sparse dataset



15 validated conjugated heat transfer simulations

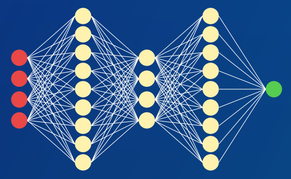
- 5 operating cases
- 3 flow rates
- 3 geometries (selected combinations, total = 15)



Training

PINN

- Governed by a zero-dimensional lumped-capacitance model
- Ordinary differential equations incorporated into loss function



15 effective heat transfer parameters

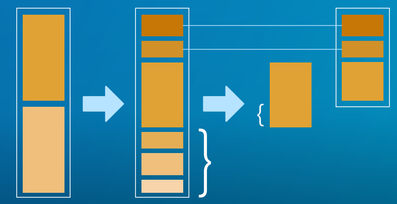
Bridge–response surface model

- Captures complex geometric dependencies
- Enables prediction of heat transfer coefficient for unseen, arbitrary geometry and flow condition

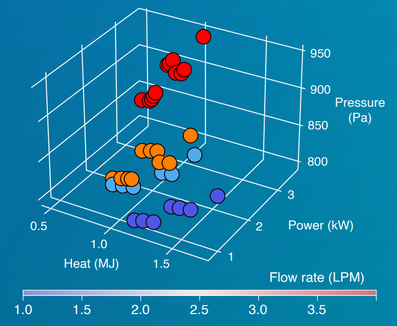
Continuous design parameters

Non-dominated sorting genetic algorithm II

- Autonomous exploration of design space
- Minimizes pressure drop while maximizing discharge heat and average power



Multi-objective design optimization



$R^2 > 0.999$ and matched the best baseline at much lower pumping power

The proposed framework represents a powerful tool for achieving globally optimized, high-performance, and cost-effective design configurations for LHTES systems

Physics-Informed Neural Networks for Multi-Objective Design Optimization of Latent Heat Thermal Energy Storage Systems
Han *et al.* (2026) | *Journal of Energy Storage* | DOI: 10.1016/j.est.2026.122514

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