



Research Paper

A novel 3D thermal network model and multi-criteria optimisation of hybrid battery thermal management systems for electric vehicles

A. Afass^{a,*}, B. Lamrani^b, M.A. Tankari^c, M. Karkri^c, S. Landini^d, T. Kousksou^a^a Université de Pau et des Pays de l'Adour, E2S UPPA, SIAME, Pau, France^b Mohammed V University in Rabat, Faculty of Sciences, MANAPSE Laboratory, Rabat, 1014 RP, Morocco^c Université Paris Est Creteil, CERTES, F-94010, Creteil, France^d School of Engineering, Mathematics and Physics, University of East Anglia, Norwich, NR4 7TJ, United Kingdom

ARTICLE INFO

Keywords:

Battery
Optimisation
BTMS
PCM
Thermal network
MCDM

ABSTRACT

Thermal management of lithium-ion batteries under high-load conditions remains a critical bottleneck for the safe operation of electric vehicles. Current multi-criteria decision-making (MCDM) optimisation frameworks rely on computational fluid dynamics (CFD) or data-dependent surrogate models, severely limiting the range of design variables that can be explored. This paper proposes a novel, large-scale MCDM optimisation framework for a hybrid BTMS combining phase change material (PCM) and liquid cooling. A transient, 3D lumped thermal network model for a battery pack is developed and validated, enabling rapid and accurate evaluation of 78,000 distinct design configurations. The framework optimises seven design variables, including geometrical and flow control parameters, across three liquid cooling architectures and 26 PCMs, against four quantitative and eight qualitative, conflicting criteria. By coupling the TOPSIS ranking approach with six distinct weighting methods, the study reveals that the C₁ liquid cooling configuration, with a counter-current middle tube layer, shows better heat dissipation than the two other arrangements. Furthermore, organic PCM A28 emerges as the optimal thermal buffer across multiple weighting approaches under the current testing conditions. Spearman correlation analysis reveals strong rank alignment (>0.9) among the MEREC, AHP, and SWARA weighting methods. Ultimately, the proposed 3D model offers an agile and robust alternative for performing large-scale optimisation of hybrid BTMS.

1. Introduction

The ongoing energy crisis and its environmental repercussions [1,2], together with the geopolitical instability affecting energy markets [3], have accelerated the shift to electric vehicles (EVs) as a realistic solution for the transportation sector [4]. Lithium-ion batteries (LIBs) serve as the dominant energy source for EVs due to their high energy density, low self-discharge rate, and long cycle life [5]. However, the electrochemical reactions within LIBs are extremely sensitive to temperature variations [6]. LIBs operated outside their safe operational window, typically between 15 °C and 45 °C, experience faster capacity degradation and reduced lifespan [7]. For better long-term capacity retention and better electrochemical performance, it is highly recommended to keep the temperature within a narrower range of 15 °C to 35 °C [8]. Additionally, an asymmetrical temperature distribution between cells within the same battery pack provokes an uneven ageing process, which can cause

performance degradation over time. Therefore, it is recommended to keep the temperature difference between cells inside the battery pack no more than 5 °C [9]. Consequently, a reliable battery thermal management system (BTMS) should be developed to ensure safe operating conditions, especially for high-rate discharging [10].

Current commercial BTMSs rely massively on liquid cooling systems, while pioneer EVs employed air cooling [11]. In literature, air, liquid, and phase change material (PCM) based systems are extensively studied [12]. Air cooling is simple in design, lightweight, highly reliable, and cost-effective due to the complete absence of leakage risks. However, its inherently low specific heat capacity and poor thermal conductivity severely restrict its heat dissipation capabilities [13]. This method is inadequate for high-load scenarios or densely packed modules, where it struggles to prevent hotspots or restrain thermal runaway propagation. Attempting to overcome this limitation by forcing higher air velocities introduces new challenges in the form of higher power consumption from fans and disruptive noise generation [14].

* Corresponding author.

E-mail address: aafass@univ-pau.fr (A. Afass).<https://doi.org/10.1016/j.applthermaleng.2026.133587>

Received 12 July 2026; Received in revised form 4 October 2026; Accepted 8 October 2026

Available online 15 October 2026

1359-4311/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Nomenclature*Abbreviations*

AHP	Analytic hierarchy process
AMGA	Archive-based micro genetic algorithm
ANN	Artificial neural network
BPNN	Back propagation neural network
BTMS	Battery thermal management system
CC	Cell-to-cell distance
CFD	Computational fluid dynamics
CRITIC	Criteria importance through intercriteria correlation
CT	Cell-to-tube distance
CV	Control volume
ED	Energy density
EV	Electric vehicle
EWM	Entropy weight method
GA	Genetic algorithm
HTC	Heat transfer coefficient
LC	Liquid cooling
LHS	Latin hypercube sampling
LIB	Lithium-ion battery
MAE	Mean absolute error
MCDM	Multi-criteria decision-making
MEREC	Method based on the Removal Effects of Criteria
NIS	Negative ideal solution
NSGA-II	Non-dominated Sorting Genetic Algorithm II
ODE	Ordinary differential equation
PCM	Phase change material
PIS	Positive ideal solution

RBF	Radial basis function
RMSE	Root mean square error
RSM	Response surface methodology
SCC	Spearman correlation coefficient
SWARA	Stepwise weight assessment ratio analysis
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	Vlsekriterijumska Optimizacija I Kompromisno Resenje

Symbols

it	Index of liquid cooling tube in x-direction
T_{max}	Maximum cell temperature ($^{\circ}\text{C}$)
ΔT_{max}	Maximum thermal gradient ($^{\circ}\text{C}$)
Δt	Time step (s)
γ	Supercooling
δ	Mass ratio
ζ	Flammability
θ	Thermal stability
λ	Thermal conductivity
ξ	Corrosiveness
o	Environment
ϖ	Toxicity
ρ	Density
ϱ	Recyclability
ϕ	Cost
a_0, a_1, a_2	Rule-based liquid cooling velocity control coefficients
V_{max}	Maximum flow velocity (m/s)
K	Coolant inlet temperature factor ($^{\circ}\text{C}$)

Liquid cooling (LC) often functions on a water-glycol mixture, which exhibits excellent heat transfer capabilities and high heat capacity. Researchers quantify the value of the heat transfer coefficient (HTC) of air cooling between 4.2 and 80.3 W/m².K, while for LC systems it is confined between 11.7 and 1020.2 W/m².K [15], making it the commercial standard for high-performance EVs [16]. Due to the immense heat dissipation, it ensures temperature uniformity even in densely packed modules. However, such an approach comes at the cost of BTMS complexity, weight, and manufacturing and maintenance expenses. Crucially, circulating liquid coolants in between cells introduce leakage risks that can cause electrical short circuits. The pumps and compressors required for system operation consume a significant amount of energy from the onboard LIBs [17].

The passive PCM-based BTMS provides exceptional temperature uniformity in a compact and static design, with an HTC value estimated in the range between 7.1 and 861.7 W/m².K for hybrid PCM-based systems [15]. By absorbing the generated LIB heat during phase transitions, it requires zero external power and depends solely on intrinsic latent heat properties [18]. Despite these advantages, the thermal conductivity of pure PCMs severely limits their heat transfer capabilities, meaning they are not suited for high load cases such as fast charging [14]. Additionally, latent heat capacity is bounded to a finite value, once the PCM is fully melted during continuous high-rate operation, it becomes a thermal insulator [19]. Furthermore, PCMs present different challenges, notably volume expansion, supercooling, flammability, and leakage risks [20].

To overcome the limitations of each technology, hybrid BTMS integrating multiple cooling strategies has emerged as a promising solution to meet all performance objectives under high load conditions [21]. Hybrid architectures can combine active-active, passive-passive, or active-passive methods to leverage their respective strengths [22]. In the literature several hybrid configurations were proposed notably, liquid and air cooling [23], heat pipe and liquid cooling [24], and composite

PCM and heat pipe [25]. While those systems are effective, PCM-based hybrid architectures performance is exceptionally superior to the other ones [26]. In these coupled systems, the PCM acts as an immediate thermal buffer to ensure temperature uniformity by absorbing abrupt heat spikes, while an active system extracts the accumulated heat to regenerate the PCM's latent capacity [27]. Hybrid PCM and liquid cooling are widely considered the most effective solution for extreme load conditions [28]. Several studies indicate that it maintains a maximum battery temperature strictly within the 15 $^{\circ}\text{C}$ –40 $^{\circ}\text{C}$ range under different conditions, while keeping cell-to-cell temperature differences well below 5 $^{\circ}\text{C}$ as recommended [22].

To enhance the performance of BTMS and reduce energy consumption, researchers optimised different BTMS variables ranging from PCM thermal properties to liquid cooling designs [29]. The optimisation process involves structural, material, and operational parameters [30]. In hybrid strategies, maximising heat dissipation and temperature uniformity against minimising system weight and pump power is the most desirable scenario [31]. A major limitation in the current literature is the heavy reliance on computational fluid dynamics (CFD) models for system optimisation, that's why new studies employ surrogate models to conduct parametric multi-objective optimisation [32,33].

Zheng et al. [34] developed an artificial neural network (ANN) based on 30 CFD data results, from which a genetic algorithm (GA) is employed to optimise channel spacing, vapor chamber height, and coolant flow velocity based on battery maximum temperature, temperature gradient within the battery module, and system energy density. The neural network model's results were subjectively weighted through the analytic hierarchy process (AHP) and ranked according to technique for order preference by similarity to ideal solution (TOPSIS) for the selection of the optimal design variable values. Bai et al. [35] developed a back propagation neural network (BPNN) and the non-dominated sorting genetic algorithm II (NSGA-II) to examine battery pack geometrical parameters and liquid coolant network designs. The entropy weight

method (EWM) TOPSIS method was used to select the optimal design based on maximum temperature and minimal flow pressure drop. Liu et al. [36] applied a radial basis function (RBF) model and the archive based micro genetic algorithm (AMGA) to optimise a hybrid PCM liquid cooling system by adjusting channel height, coolant inlet velocity, and inlet temperature values. To balance the thermal performance and pump power, the EWM-TOPSIS method was applied to objectively identify the optimal design variable values. By coupling a Kriging model with the NSGA-II algorithm, Yang et al. [37] optimised a hybrid heat pipe and liquid cooling BTMS by assessing liquid cooling circuit related parameters. The EWM-TOPSIS method was implemented to find the best design variable values to compromise between thermal performance and pressure drop. By applying the same methodology to a liquid cooling BTMS of 16 cylindrical cells, Wu et al. [38] proposed a lightweight system while maintaining optimal thermal performance. Sharma et al. [39] employed qualitative and quantitative outputs to rank seven distinct liquid cooling architectures by employing VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) multi-criteria decision-making (MCDM). The decision matrix includes quantitative thermo-hydraulic factors (system weight, thermal performance, and pressure drop) with qualitative BTMS design criteria (manufacturability, maintenance, and safety characteristics).

The existing literature reveals two major drawbacks in current BTMS optimisation frameworks. First, researchers rely on CFD models to evaluate thermal-hydraulic outputs [40]. However, CFD simulations are computationally expensive, which restricts the number of design variables that can be explored drastically [41,42]. While surrogate based neural network models (ANN, BPNN, RSM, Kriging) offer computation advantages, their predictive accuracy remains bound to their training data [43]. It requires massive datasets to train effectively, and methods such as RSM often struggle to accurately capture the highly non-linear, multi-variable relationships inherent to complex hybrid BTMS [44]. Consequently, the reliance on either CFD or surrogate models significantly hinders the scope and accuracy of massive-scale MCDM optimisation [45].

To circumvent these computational constraints, researchers adopted reduced-order electro-thermal and thermal resistance network models. While these methods mitigate computational costs, their use in modelling BTMS for battery pack level exhibits some limitations. A set of existing investigations is constrained to single-cell domains or simplified 1D approximations [46–48], which fail to capture multi-directional temperature evolution in cell and pack level. Even when scaled to the pack level, studies modelling complex hybrid PCM-liquid systems often remain confined to 1D simulations [49]. When spatial resolution is advanced to 2D projections, the literature includes pack-level evaluations of passive stagnant air cooling [50], pure liquid cooling [51], and hybrid PCM-liquid cooling [52]. However, 2D models cannot represent the thermal performance of a BTMS through multi-layer LC. Consequently, the development of a 3D thermal network capable of coupling PCM with LC at the pack level is absent from literature. In addition to this modelling gap, the optimisation of PCM-based hybrid BTMS is currently profoundly biased towards quantitative thermophysical properties within a constrained material sample size [53].

To bridge these gaps, this study proposes a large-scale hybrid MCDM optimisation framework for a hybrid PCM-liquid cooling BTMS. The novelty of this work lies in its 3D architectural execution of the whole BTMS and integration into an MCDM framework. This approach maintains acceptable accuracy while operating at a low computational cost, enabling the simulation of 1000 distinct design cases, which expand to 78,000 distinct hybrid BTMS configurations when combined with the 26 PCMs and the three LC arrangements. By coupling the TOPSIS ranking approach with different weighting methods, this study performs a global optimisation of 7 design variables based on 12 quantitative and qualitative criteria. The developed framework is adequate for massive parametric evaluation without bearing the accuracy loss, or massive pre-training data requirements typical of surrogate neural networks.

This paper is structured as follows: Section 2 details the physical formulation of the 3D thermal network model and the MCDM methodology, encompassing the criteria weighting and TOPSIS ranking procedures. Section 3 presents the validation of the proposed model against experimental and CFD data. Section 4 discusses the optimisation results, and the analysis of weighting methods impacts on the selection of the optimal BTMS design. Finally, Section 5 summarises the core findings of the work and outlines perspectives for future research.

2. Methodology

2.1. Physical model

The proposed hybrid BTMS, integrating PCM with active LC is composed of 24 cylindrical lithium-ion cells, distributed as 4 parallel rows with 6 cells in each row (see Fig. 1). The cells are commercial 21,700-type with a nominal capacity of 4 Ah, as listed in Table 1. To ensure efficient heat extraction, LC tubes are interleaved between the cell rows in a horizontal serpentine layout. This active cooling network is evenly distributed across three distinct vertical layers. While the PCM fills the bulk of the battery pack to absorb the heat from the cells before it gets transferred by the active fluid circulation outside the pack. The fluid employed for the LC is a mixture of water and ethylene glycol. The physical properties of this mixture, given as functions of temperature expressed in degrees Celsius, are provided in Table 2.

Three LC configurations were tested in this work, each differing in how the second tube layer is arranged. In the first case (C_0), all three vertical tube layers are identical, and operate in a parallel, co-current flow regime. The coolant enters from the same inlet side on the right face of the battery pack in every layer (see Fig. 2(a)). The second configuration (C_1) reverses the coolant flow of the middle tube layer relative to the top and bottom layers. The coolant inlet of the second layer is positioned in the left side of the battery pack and exits from the other side (see Fig. 2(b)). For the third configuration (C_2), the coolant enters from the same face for all three layers, maintaining an overall co-current flow direction (see Fig. 2(c)). However, the physical layout of the middle tube layer is shifted along the x-axis. By displacing the coolant inlet to the adjacent cell row, the entire serpentine path is staggered relative to the upper and lower layers.

To rigorously assess the thermal performance of the proposed hybrid BTMS under extended operation duration, the battery pack is subjected to three consecutive high-load charge and discharge cycles. Each cell undergoes a 4C discharge and a 3C charge, separated by a 10 min resting period (see Fig. 3). This current profile reflects high load operating conditions that are encountered during driving and charging modern EVs. The battery pack is maintained in a controlled ambient environment of 25 °C, with thermal insulation mounted on the upper and lower sides of the pack.

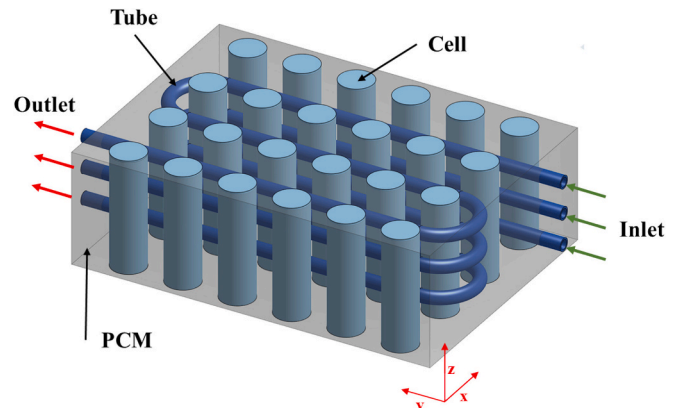


Fig. 1. Battery pack with the integrated hybrid BTMS.

Table 1
Cell characteristics [54].

Property	Value
Mass (m_{cell})	69 (g)
Diameter (d_{cell})	21.7 (mm)
Height (h_{cell})	70.9 (mm)
Nominal capacity	4 (Ah)
Nominal voltage	3.65 (V)

Table 2
Physical properties of the water-ethylene glycol mixture [55].

Property	Mathematical equations
Heat capacity ($\text{kJ.kg}^{-1}.\text{K}^{-1}$)	$C_{pLC} = 3.85 \times 10^{-3}T_{LC} + 3.203$
Density (kg.m^{-3})	$\rho_{LC} = -0.387T_{LC} + 1081$
Dynamic viscosity (Pa. s)	$\mu_{LC} = 5.864 \times 10^{-6}T_{LC}^2 - 3.489 \times 10^{-4}T_{LC} + 8.36 \times 10^{-3}$
Heat conductivity ($\text{W.m}^{-1}.\text{K}^{-1}$)	$\lambda_{LC} = 8.3 \times 10^{-4}T_{LC} + 3.64 \times 10^{-1}$

2.2. Numerical model

The lumped thermal resistance-capacitance network approach was used to investigate the hybrid BTMS. To develop the numerical model, some assumptions were considered. For instance, the water-glycol mixture is considered an incompressible and Newtonian fluid. The radiative heat transfer is considered negligible because of the low temperature of the batteries. Natural convection in the molten PCM is

neglected here for three reasons. The battery pack is compact and the cells are evenly spaced, so heat is generated uniformly throughout the battery pack. The PCM fills the narrow spaces between cells, which limits convective flow from developing. Finally, the thermal load is linked to transient charge/discharge, providing limited time for a convective regime to fully establish. A scale analysis based on the Rayleigh number, reported in the Limitations section (Section 4.6), shows that the liquid PCM remains close to a conduction-dominated regime in the cell-to-tube gaps that control heat extraction towards the LC tubes, whereas natural convection may develop in the widest cell-to-cell gaps once the PCM is fully molten. The thermophysical properties of the cell and PCM are isotropic and temperature-independent, though PCM properties are given as a function of phase state outside the transition window, while during the phase-transition window they are given as a function of liquid fraction. The temperature independence of the thermophysical properties is justified over the narrow operating window considered in this work (25–45 °C), within which the property value variations remain small. As demonstrated by the work of Cailliez et al. [56], the variation of heat capacity and radial and axial thermal conductivity in the range of 0–40 °C is less than 7.4%, 11% and 6.5%, respectively. In the narrow window between 20 and 40 °C, this variation in thermal properties is reduced further, with less than 4%, 5.7% and 5.3% for heat capacity, radial and axial thermal conductivity, respectively [56].

After considering these assumptions, the computational domain was discretised into a 3D grid of isothermal control volumes (CVs). The spatial discretisation is constructed to reflect the macroscopic physical topology of the battery pack. While further refining the spatial grid will

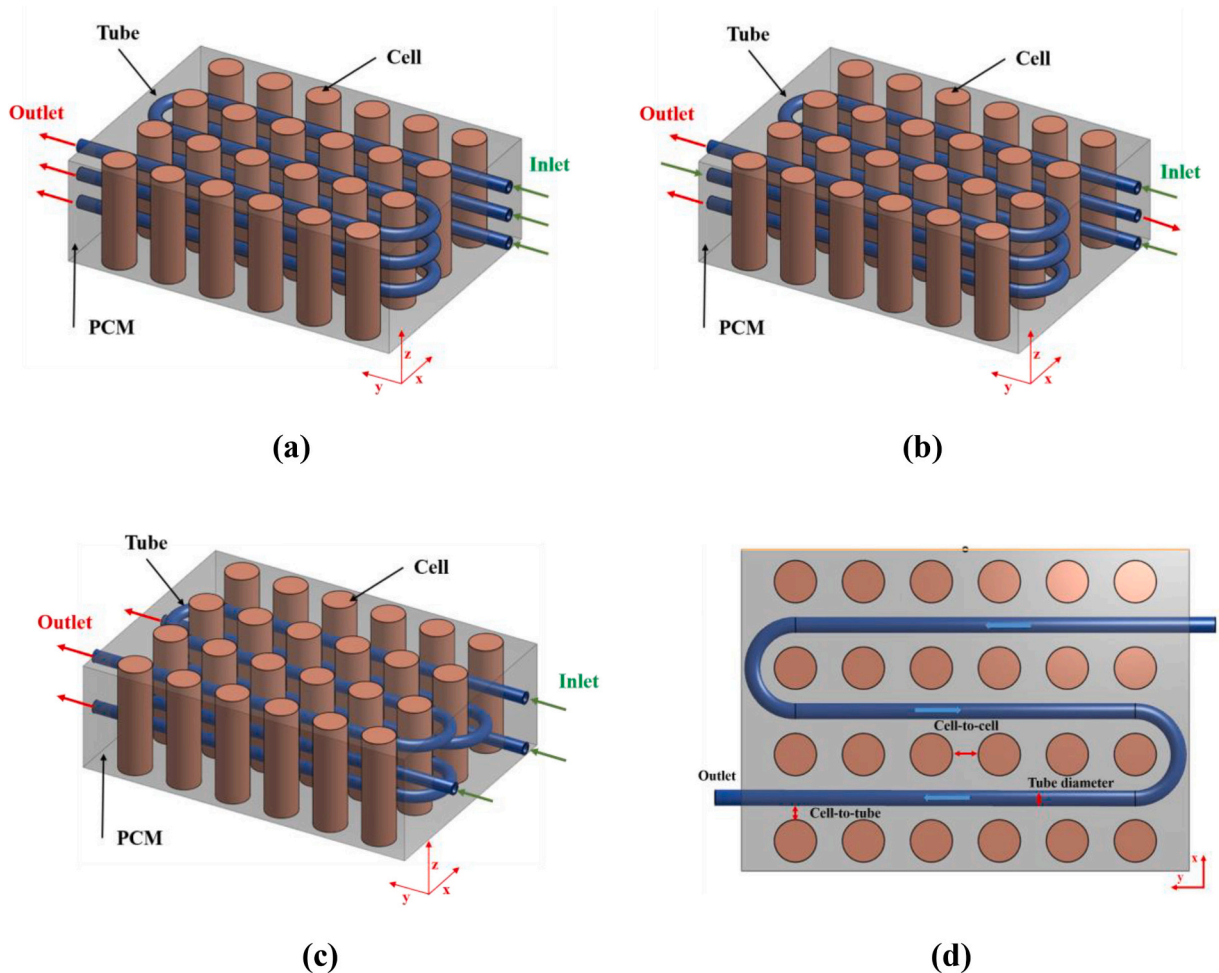


Fig. 2. Battery pack configuration with the different liquid cooling configurations: (a) C₀, (b) C₁, (c) C₂, (d) cross section of C₀.

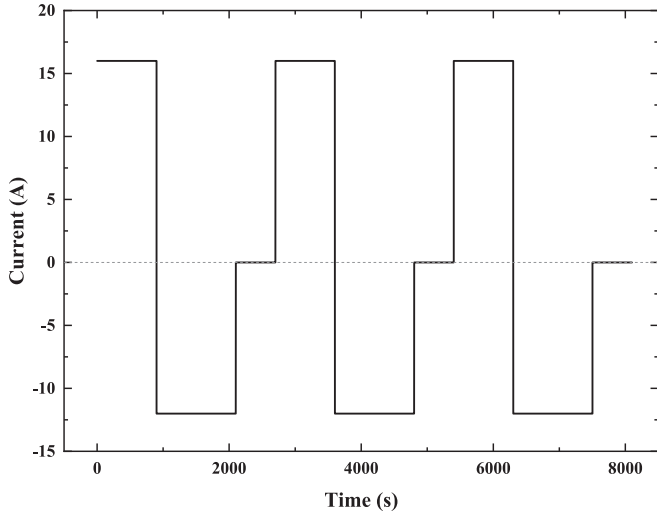


Fig. 3. Current profile applied during the assessment of the hybrid BTMS.

increase the sensitivity of the temperature field, it will also raise the computational overhead without providing significant macroscopic thermal insights. Therefore, the current spatial discretisation offers a balance between predictive fidelity and low computational cost. In the horizontal plane, the battery pack is partitioned in a way that each CV encapsulates one single lithium-ion cell and portion of PCM. This spatial discretisation is efficient in capturing the local heat exchange between cell-PCM systems, and it allows us to identify the thermal gradient in the horizontal plane. Consequently, the 24 cells packed in it are segmented into $N_x = 4$ and $N_y = 6$ CVs along the horizontal plane. Similarly, to accurately characterise the vertical thermal gradients induced by the active liquid cooling tubes, the height of the battery pack is vertically segmented into three identical layers ($N_z = 3$), each with a height of 23.63 mm. For the LC layout in the horizontal plane, as there are only three tube rows along the x-direction, the N_{tubes} is set to 3. Ultimately, the total number of temperature states for the BTMS is the sum of the battery nodes, PCM nodes, and LC nodes: $N_{\text{states}} = (N_x N_y N_z)_{\text{battery}} + (N_x N_y N_z)_{\text{PCM}} + (N_{\text{tubes}} N_y N_z)_{\text{LC}} = 198$. The physical dimension of a single CV for the three-space direction is defined as $L_x = d_{\text{cell}} + d_{\text{tube}} + 2d_{\text{cell-tube}}$, $L_y = d_{\text{cell}} + d_{\text{cell-cell}}$, and $L_z = h_{\text{cell}}/3$. With $d_{\text{cell-tube}}$ is the

distance between cell and tube in the x-direction, and $d_{\text{cell-cell}}$ is the distance in the y-direction between two consecutive cells.

2.2.1. Governing equations

To describe the heat transfer inside the cell-PCM-LC system, the transient energy balance equation is applied for each CV. As illustrated in the schematic of the equivalent thermal network, (see Fig. 4), the battery pack is represented as an interconnected network of thermal resistors, capacitors, and heat sources. These nodes are connected via multi-directional heat resistances, which represent the interfaces where thermal energy is exchanged.

• Battery domain

The thermal behaviour of LIB in each CV is governed by the energy conservation equation, balancing transient thermal storage, heat generation, and conduction to adjacent cell nodes and the surrounding PCM:

$$m_b C_{p,\text{cell},ijk} \frac{dT_{\text{cell},ijk}}{dt} = Q_{\text{gen},ijk} + \sum \frac{T_{\text{cell},\text{neighbour}} - T_{\text{cell},ijk}}{R_{\text{th},\text{cell-cell}}} + \frac{T_{\text{PCM},ijk} - T_{b,ijk}}{R_{\text{th},\text{cell-PCM}}} \quad (1)$$

where m_b is the mass of the cell in a given CV, $C_{p,b,ijk}$ is the specific heat capacity. $R_{\text{th},\text{cell-cell}}$ and $R_{\text{th},\text{cell-PCM}}$ represent the thermal resistance for cell-cell conduction along the vertical direction and cell-PCM heat transfer within the CV, respectively. As each cell is divided into three segments along the z-axis, the number of adjacent cell nodes depends on the position of CV along the vertical direction.

The internal heat generation of a cell consists of reversible and irreversible heat. In this study, the battery pack is operated under high C-rate, where irreversible phenomenon dominates the thermal behaviour [57]. The irreversible heat generation includes ohmic losses, activation, concentration losses, and heat of mixing [58]. At higher operating C-rate the contribution of the irreversible heat dominates the overall heat generation of the cell [59]. Chen et al. [60] found for a similar cell, that the contribution of reversible heat remains below 5% of total heat generation when the current load is above 1C rate. In addition, the reversible entropic heat changes sign between charge and discharge, so that its net contribution largely cancels over a complete cycle, whereas the irreversible heat always accumulates. Its maximum influence on the predicted temperatures is estimated in the Limitations section (Section 4.6). The internal heat generation $Q_{\text{gen},ijk}$ is numerically

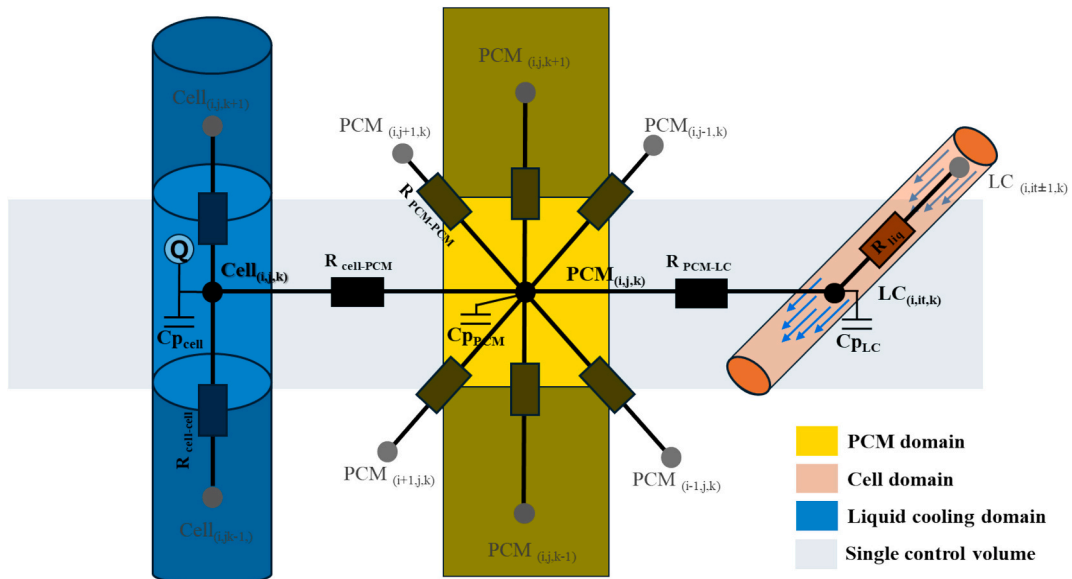


Fig. 4. Thermal network model of the hybrid BTMS.

represented by ohmic heating due to the internal resistance as follows:

$$Q_{gen_{ijk}} = \frac{I^2 R_0 (T_{cell_{ijk}})}{N_z} \quad (2)$$

where I is the applied current and $R_0 (T_{cell_{ijk}})$ is the averaged internal equivalent resistance of the cell modelled as third-order polynomial of nodal cell temperature given as [61]:

$$R_0 (T_{cell_{ijk}}) = (12.407 - 0.5345 \cdot T_{cell_{ijk}} + 0.0134 \cdot T_{cell_{ijk}}^2 - 0.0001 \cdot T_{cell_{ijk}}^3) \times 10^{-3} [\Omega] \quad (3)$$

• PCM domain

The PCM absorbs the excessive heat from the LIB and exchanges heat with the surrounding PCM nodes in the three cartesian directions. The transient energy balance equation also accounts for the LC system, resulting in a mathematical formulation in the form of:

$$m_{PCM_{ijk}} C_{p_{PCM_{ijk}}} \frac{dT_{PCM_{ijk}}}{dt} = \sum \frac{T_{PCM_{neighbour}} - T_{PCM_{ijk}}}{R_{th_{PCM-PCM}}} + \frac{T_{cell_{ijk}} - T_{PCM_{ijk}}}{R_{th_{cell-PCM}}} + \frac{T_{LC_{it,jk}} - T_{PCM_{ijk}}}{R_{th_{LC-PCM}}} + \frac{T_{ext} - T_{PCM_{ijk}}}{R_{th_{PCM-ext}}} \quad (4)$$

The conductive heat transfer between the adjacent PCM thermal nodes is represented by the equivalent thermal resistance $R_{th_{PCM-PCM}}$. In this study the value of the thermal resistance is computed separately for each direction, to consider the physical constraint of the meandering LC tubes and cell volume in each CV.

$$R_{th_{PCM-PCM}} = \begin{cases} R_{th_{x_{PCM-PCM}}} = \frac{L_x}{k_{PCM}(L_y L_z - L_y d_{tube})} \\ R_{th_{y_{PCM-PCM}}} = \frac{L_y}{k_{PCM}(L_x L_z)} \\ R_{th_{z_{PCM-PCM}}} = \frac{L_z}{k_{PCM}(L_y L_x - A_{cell_{hor}})} \end{cases} \text{ with } A_{cell_{hor}} = \pi \left(d_{cell}/2 \right)^2 \quad (5)$$

The convective heat transfer between the PCM and the coolant circuit in each CV is characterised by the thermal resistance calculated as:

$$R_{th_{PCM-LC}} = \frac{1}{h_{liq} A_{tube-contact}} = \frac{2}{h_{liq} (\pi \cdot d_{tube} \cdot L_y)} \quad (6)$$

The outer surface of the battery pack exchanges heat with the surrounding air by natural convection. The typical value of the natural convection HTC is between $1 - 10 \text{ W/m}^2\text{K}$ [62]. The value of the HTC for the lateral sides of the battery pack is set to $h = 5 \text{ W/m}^2\text{K}$, while for the bottom and top surfaces $h = 1 \text{ W/m}^2\text{K}$ was adopted. The values provided for the ambient HTC remain constant for the entire study.

To account for the latent heat absorption during the solid-liquid phase transition of the PCM, the apparent heat capacity function is used [63]:

$$C_{p_{PCM}}(T_{PCM}) = C_{sensible}(T_{PCM}) + L_s \frac{\frac{2\beta}{\Delta T}}{\pi \left(\left((T_{PCM} - T_m) \left(\frac{2\beta}{\Delta T} \right) \right)^2 + 1 \right)} \quad (7)$$

with, ΔT is the temperature difference between the liquidus and the solidus temperatures (i.e. T_{liq} and T_{sol}) of the PCM, T_m is the melting temperature of the PCM, while β is the dimensionless inclination set to a value of 3.1. $C_{sensible}(T_{PCM})$ represent the sensible heat capacity defined as [63]:

$$C_{sensible}(T_{PCM}) = C_l(T_{PCM}) \cdot f(T_{PCM}) + C_s(T_{PCM}) \cdot (1 - f(T_{PCM})) \quad (8)$$

where $f(T)$ is the liquid fraction defined by the following expression [64]:

$$f(T_{PCM}) = \frac{1}{\pi} \left[\arctan \left(\frac{2\beta(T_{PCM} - T_m)}{T_{liq} - T_{sol}} \right) + \frac{\pi}{2} \right] \quad (9)$$

• Liquid cooling domain

The active cooling network is governed by advective heat transport along the flow direction and convective heat transfer with the surrounding PCM. For a given fluid node, the transient energy balance is:

$$m_{LC} C_{p_{LC_{it,jk}}} \frac{dT_{LC_{it,jk}}}{dt} = \dot{m} C_{p_{LC_{it,jk}}} (T_{LC_{it,in,k}} - T_{LC_{it,jk}}) + h_{liq} A_{contact} (T_{PCM_{ijk}} - T_{LC_{it,jk}}) \quad (10)$$

where $\dot{m}$ is the mass flow rate and $T_{LC_{it,in,k}}$ is the temperature of the liquid inlet for a given CV. For simplicity, the inlet temperature of the coolant is equal to the temperature of coolant in the previous CV depending on flow direction $T_{LC_{it,in,k}} = T_{LC_{it,j-1,k}}$. The water-glycol mixture flow is dynamically controlled and the value of the HTC between PCM and liquid cooling tube is defined using Dittus-Boelter correlation [65]:

$$h_{liq} = \frac{\lambda_c}{d_{tube}} \begin{cases} 3.66 & \text{for laminar flow (Re} < 2300) \\ 0.023 \text{Re}^{0.8} \text{Pr}^{0.4} & \text{for turbulent flow (Re} \geq 2300) \end{cases} \quad (11)$$

The coolant velocity is provided as function of the maximum temperature of the cell in the battery pack. This rule-based coordination of the velocity is proposed to lower active energy part of the hybrid BTMS.

$$\begin{cases} |(T_{max} - 25)| < 5 & V_{inlet} = a_0 V_{max} \\ |(T_{max} - 25)| < 10 & V_{inlet} = a_1 V_{max} \\ |(T_{max} - 25)| \geq 10 & V_{inlet} = a_2 V_{max} \end{cases} \quad (12)$$

with the maximum flow velocity is set to $V_{max} = 0.6 \text{ m/s}$. The coefficient a_0 , a_1 and a_2 are set between 0 and 1, further detail concerning the control strategy coefficient designation will be defined in Section 2.3 (Eq. (25)).

2.2.2. Numerical solution

By assembling the discrete CV energy balances, the entire 3D thermal network is notated into continuous-time state-space representation. The first-order ordinary differential equation (ODE) governing the complete system is expressed in matrix notation as:

$$\frac{dT}{dt} = C^{-1} (GT + B_{amb} + Q_{gen}) \quad (13)$$

where, T is the temperature vector of $N_{states} = 198$ length. Elements from 1 to 72 represent the temperature of all battery pack cells, while from 73 to 144 refers to PCM temperature, with elements 145 to 198 representing the coolant temperatures.

$$T = \begin{bmatrix} T_1 = T_{cell_1} \\ \vdots \\ T_{73} = T_{PCM_1} \\ \vdots \\ T_{145} = T_{LC_1} \\ \vdots \end{bmatrix} \quad (14)$$

C is the diagonal matrix containing the thermal mass of all CV domain. In this matrix the PCM corresponding value is dynamically updated to account for phase change phenomenon as described previously.

$$C = \begin{bmatrix} m_b C_{p,b} & 0 & 0 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 & 0 \\ 0 & 0 & m_{PCM} C_{p,PCM} & 0 & 0 & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & m_{LC} C_{p,LC} & 0 \\ 0 & 0 & 0 & 0 & 0 & \ddots \end{bmatrix} \quad (15)$$

$\mathbf{G}$ is the global conductance matrix, the off-diagonal terms represent the heat transfer between adjacent thermal nodes. For instance, $G_{i,j}$ is the thermal conductance between adjacent nodes i and j , comprising cell-cell, cell-PCM, PCM-PCM, PCM-LC, and LC-LC equivalent thermal conductance in one formulation. In conduction and convection cases the elements $G_{i,j}$ and $G_{j,i}$ are equal, unlike the advection equivalent conductance as it is characterised by fluid flow direction.

$$G = \begin{bmatrix} -\sum G_{1,1} & \cdots & G_{1,73} & \cdots & G_{1,145} & \cdots \\ \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ G_{73,1} & \vdots & -\sum G_{73,73} & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ G_{145,1} & \vdots & \vdots & \vdots & -\sum G_{145,145} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad (16)$$

The heat generation from the Lithium-ion cells is listed in the vector $\mathbf{Q}_{gen}$. While the ambient conditions surrounding the battery pack are included in the vector $\mathbf{B}_{amb}$.

The discrete state space formulation for the thermal behaviour of the hybrid BTMS presented allows for seamless computation efficiently for the different LC configurations. To solve the system a first order forward-difference approximation is applied to the time derivative. The fully explicit Euler approach avoids the immense computational overhead of inverting non-linear sparse matrices at every time step, which would otherwise be required by exact analytical matrix-exponential solvers [66]. The iterative solution of the BTMS temperature is given as follows:

$$\mathbf{T}(t + \Delta t) = \mathbf{T}(t) + \Delta t [\mathbf{C}^{-1}(t) \cdot (\mathbf{G}(t) \cdot \mathbf{T}(t) + \mathbf{B}_{amb} + \mathbf{Q}_{gen}(t))] \quad (17)$$

A known limitation of the explicit Euler method is conditional stability, if the time step Δt is inadequate to capture the physical phenomenon, the numerical solution will oscillate and diverge to infinity.

In this work, a rigorous adaptive time-stepping algorithm is implemented. To justify this strategy, the linear stability of the explicit Euler scheme is analysed. A clear distinction is made here between the continuous system matrix $\mathbf{A} = \mathbf{C}^{-1} \cdot \mathbf{G}$, which governs the ODE system of Eq. (13), and the discrete state-transition matrix $\mathbf{M} = \mathbf{I} + \Delta t \mathbf{A}$, which advances the explicit solution of Eq. (17) from one time step to the next: $\mathbf{T}^{n+1} = \mathbf{M} \mathbf{T}^n + \Delta t \mathbf{C}^{-1} (\mathbf{B}_{amb} + \mathbf{Q}_{gen})$, where $\mathbf{I}$ is the identity matrix. The explicit scheme is stable if the spectral radius of the transition matrix does not exceed unity, $\rho(\mathbf{M}) = \max_i |1 + \Delta t \lambda_i| \leq 1$, where λ_i are the eigenvalues of $\mathbf{A}$ (λ_i and ρ denote eigenvalues and spectral radius, and must not be confused with the thermal conductivity and density). For conduction and convection exchanges, $\mathbf{G}$ is symmetric and $\mathbf{A}$ is similar to the symmetric negative semi-definite matrix $\mathbf{C}^{-1/2} \mathbf{G} \mathbf{C}^{-1/2}$; its eigenvalues are therefore real and non-positive ($\lambda_i = -|\lambda_i| \leq 0$), and the stability condition reduces to $-1 \leq 1 + \Delta t \cdot \lambda_i \leq 1$. Isolating Δt gives an upper bound on the time step equal to twice the reciprocal of the largest eigenvalue magnitude: $\Delta t \leq \frac{2}{|\lambda_{max}|}$.

Evaluating the exact maximum eigenvalue of the system at every time step elevates the computational cost. Instead, the upper bound is established using the Gershgorin Circle Theorem [67]. It states that every eigenvalue of $\mathbf{A}$ lies within at least one Gershgorin disk D_i in the complex plane:

$$D_i = \left\{ \lambda \in \mathbb{C} : |\lambda - A_{ii}| \leq \sum_{j \neq i} |A_{ij}| \right\} \quad (18)$$

Applying the reverse triangle inequality bounds the absolute value of the eigenvalue by the center and radius of the disk: $|\lambda| -$

$|A_{ii}| \leq |\lambda - A_{ii}| \leq \sum_{j \neq i} |A_{ij}|$, lead to $|\lambda| \leq \sum_{j \neq i} |A_{ij}| + |A_{ii}|$.

The thermal conductance matrix $\mathbf{G}$ is weakly diagonally dominant, since each diagonal term $G_{ii} < 0$ is equal to minus the sum of all the conductances connected to node i (including the advective and ambient conductances). Mapping this property back to the matrix $\mathbf{A}$ generate that $\sum_{j \neq i} |A_{ij}| \leq |A_{ii}|$. Substituting this diagonal dominance condition into the eigenvalue bound, yields the maximum eigenvalue spectrum:

$$|\lambda_{max}| \leq \max_i \left(|A_{ii}| + \sum_{j \neq i} |A_{ij}| \right) \leq 2 \max_i \frac{|G_{ii}|}{C_{ii}} \quad (19)$$

Inverting Eq. (19) shows that $2/|\lambda_{max}|$ is always larger than or equal to the smallest nodal thermal time constant of the network, τ_{min} . A sufficient, and therefore conservative, stability condition is thus:

$$\Delta t \leq \min_i \frac{C_{ii}}{|G_{ii}|} = \tau_{min} \leq \frac{2}{|\lambda_{max}|} \quad (20)$$

This sufficient condition also holds when the advective conductances of the coolant network make $\mathbf{G}$ non-symmetric, so that some eigenvalues of $\mathbf{A}$ may be complex. Since $A_{ii} = G_{ii}/C_{ii} < 0$ and the off-diagonal row sum of $\mathbf{A}$ does not exceed $|A_{ii}|$, every Gershgorin disk of Eq. (18) is enclosed in the disk of centre $-1/\tau_{min}$ and radius $1/\tau_{min}$, which lies in the left half of the complex plane. For $\Delta t \leq \tau_{min}$, the eigenvalues $1 + \Delta t \lambda_i$ of the transition matrix $\mathbf{M}$ are therefore mapped inside the unit circle, which guarantees $\rho(\mathbf{M}) \leq 1$ for real and complex eigenvalues alike.

Because apparent heat capacity of the PCM and coolant velocity evolve during the simulation, the above analysis is applied locally in time, with the matrices $\mathbf{G}$ and $\mathbf{C}$ frozen at each time step. To account for the minor temporal non-linearities a safety factor is introduced, and the stability criterion is re-evaluated continuously so that the time step is updated dynamically throughout the simulation. Where the thermal time constant τ is computed at each iteration for the entire numerical domain as follows:

$$\begin{cases} \tau_i = \frac{C_{i,i}(t)}{|G_{i,i}(t)|} \\ \tau_{min} = \min(\tau_i) \end{cases} \quad (21)$$

Finally, the time step employed is defined as the minimum between the smallest nodal thermal time constant, weighted by a safety factor of 0.7, and 1 s. This formulation bounds the time step to a maximum value of 1 s and ensures that it never exceeds $0.7 \tau_{min}$, i.e. it remains at least 30% below the sufficient stability limit of Eq. (20).

$$\Delta t = \min(0.7 \cdot \tau_{min}, 1) \quad (22)$$

The simulation was parallelised and performed on the Pyrenes cluster of the Université de Pau et des Pays de l'Adour to carry out the large-scale parametric study of 78,000 different configurations. Computational nodes used were 32 CPU cores (dual 16-core Intel® Xeon® Gold 6326 processors) and 256 GB of RAM. All optimisation was performed in less than 140 h. By contrast, attempting a parametric optimisation of this size using fully resolved 3D CFD models would take months of supercomputer runtime. The proposed thermal network approach for large scale MCDM optimisation shows an immense practical advantage for designing BTMS.

2.3. MCDM optimisation methodology

This work sets out to optimise the thermal performance of the hybrid BTMS, using a multi-objective optimisation framework built around four quantitative and eight qualitative performance indicators. The quantitative benchmarks incorporate the maximum temperature of the cell (T_{max}), the maximum thermal gradient between battery pack cells (ΔT_{max}), the energy density (ED) [34], and the mass ratio (δ) of the BTMS [68]. It should be emphasised that $\Delta T_{max} = T_{max} - T_{min}$ metric, quantifying the largest temperature difference between any two cells of

the pack. The ED reflects the energy density of the whole battery pack with its BTMS. Meanwhile, the mass ratio (δ) quantifies the amount of deadweight added to the system defined as:

$$ED = \frac{\text{cells energy}}{\text{system volume}} = \frac{24 \times V_{\text{nominal}} \times \text{capacity}_{\text{nominal}}}{\text{system volume}} \quad (23)$$

$$\delta = \frac{\text{cells weight}}{\text{system weight}} \quad (24)$$

The PCMs tested in this study can be organic, bio-based or inorganic. Their corresponding qualitative criteria are listed in Table 1-A (see Appendix 1). The Saaty score 1–9 is used to scale the characteristic of the 26 PCMs considered, based on description of the literature (see Appendix 1) [69–73]. Ultimately, the objective of the MCDM optimisation is to evaluate all the parameters by classifying them as either “cost” or “benefit” attributes. The “cost” criteria, which needed to minimise, include T_{max} , ΔT_{max} , supercooling (γ), corrosiveness (ξ), toxicity (π), flammability (ζ), environment (ρ), and cost (ϕ). Conversely, the “benefit” criteria, which the MCDM seeks to maximise, encompass ED, δ , thermal stability (θ), and recyclability (ρ).

The optimisation of the BTMS depends on seven critical design variables, encompassing both the structural geometry of the battery pack and the operational parameters of the active LC (see Fig. 2(d)). Specifically, the chosen variables are the cell-to-cell distance (CC), cell-to-tube distance (CT), tube diameter (d_{tube}), the three rule-based LC velocity control coefficients (a_0 , a_1 , a_2), and the coolant inlet temperature factor K ($^{\circ}\text{C}$). To define global optimal configuration, these parameters are rigorously evaluated within the boundaries of the following operational constraints:

$$\begin{cases} 0.001 \text{ (m)} \leq CT \leq 0.005 \text{ (m)} \\ 0.002 \text{ (m)} \leq CC \leq 0.01 \text{ (m)} \\ 0.004 \text{ (m)} \leq d_{\text{tube}} \leq 0.008 \text{ (m)} \\ |T_{\text{max, battery}} - 25 (^{\circ}\text{C})| < 5 (^{\circ}\text{C}) & V_{\text{inlet}} = a_0 V_{\text{max}} & 0 \leq a_0 \leq 0.05 \\ |T_{\text{max, battery}} - 25 (^{\circ}\text{C})| < 10 (^{\circ}\text{C}) & V_{\text{inlet}} = a_1 V_{\text{max}} & a_0 \leq a_1 \leq 0.9 \\ |T_{\text{max, battery}} - 25 (^{\circ}\text{C})| \geq 10 (^{\circ}\text{C}) & V_{\text{inlet}} = a_2 V_{\text{max}} & a_1 \leq a_2 \leq 1 \\ T_{\text{inlet}} (^{\circ}\text{C}) = 25 (^{\circ}\text{C}) + K & -10 (^{\circ}\text{C}) \leq K \leq 10 (^{\circ}\text{C}) \end{cases} \quad (25)$$

The Latin hypercube sampling (LHS) method [74] was employed to generate 1000 sets of random sample points. Then, those design variables were simulated through the developed 3D thermal model, throughout all the 26 PCMs and the LC configurations (C_0 , C_1 , C_2), resulting in $m=78000$ distinct BTMS design configurations across $n=12$ conflicting criteria.

To provide a comprehensive overview of the MCDM methodology, Fig. 5 illustrates the complete workflow of the study, covering the initialisation of the parametric LHS design variables, the dynamic execution of the explicit thermal solver, the multi-criteria ranking of results across the different weighting approaches, and their validation through Spearman rank correlation.

2.3.1. Weighting methods

The assignment of criteria weights in MCDM determines the validity of the final ranking. Weighting approaches are categorised into subjective and objective paradigms [75]. This study englobes qualitative and quantitative criteria in the decision matrix, this grouping makes the results extremely sensitive towards weighting the values. While the EWM determines weights based purely on data dispersion, it ignores inter-criteria dependence, this mathematical limitation is directly

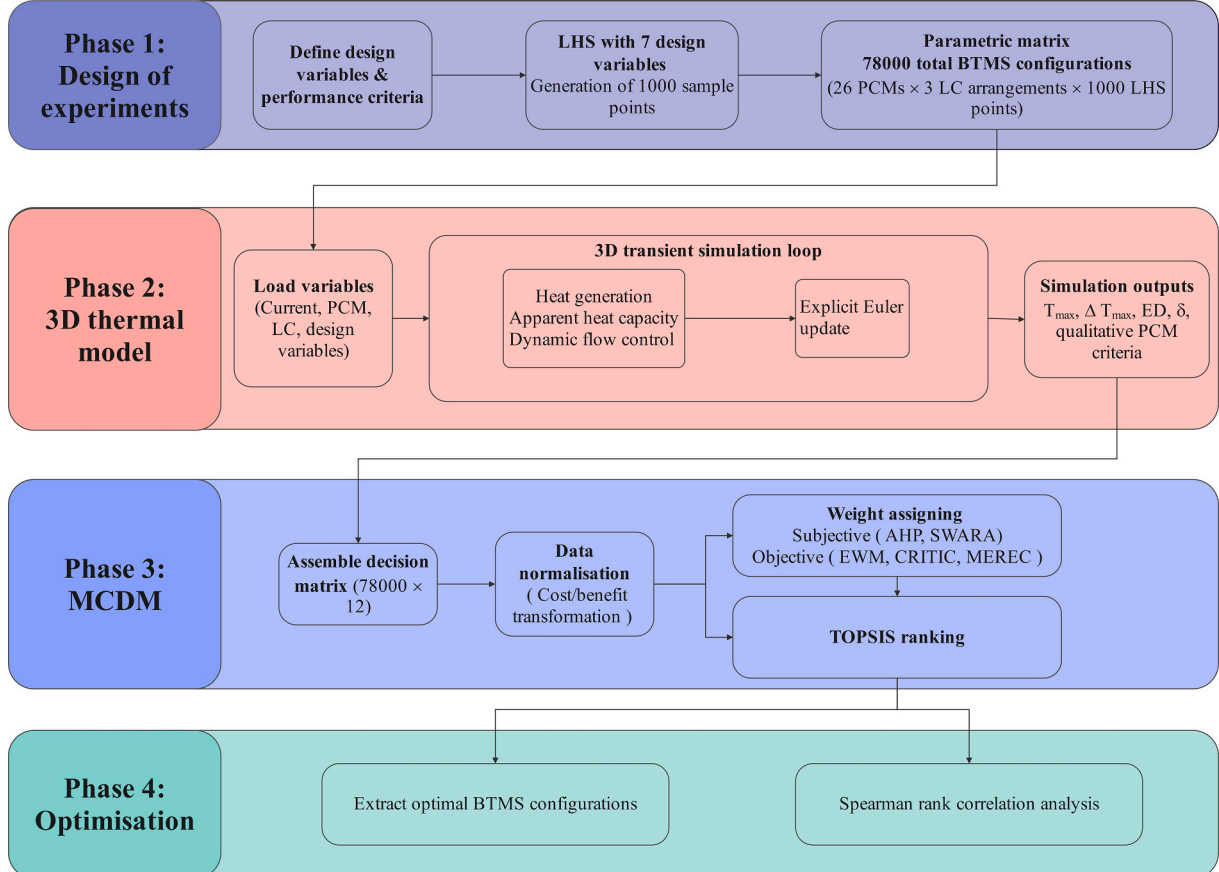


Fig. 5. Workflow proposed for BTMS optimisation.

resolved by integrating the CRITIC method. Furthermore, MEREC assesses the overall performance change when a criterion is removed from the decision matrix, offering a perspective on structural criterion importance. On the subjective side, AHP provides a consistent pairwise comparison, while SWARA is incorporated to mitigate the potential inconsistencies associated with large AHP evaluation matrices. Finally, the Equal weighting method serves as a neutral baseline. Comparing the results of all six methods quantifies how sensitive the optimal BTMS configuration is to the weighting approach [76].

• Data normalization

Because the 12 criteria encompass different units and magnitudes, the raw decision matrix $\mathbf{DM} = [x_{ij}]$ of size $m \times n$ must first be normalised. The criteria are divided into “benefit” and “cost” criteria, necessitating maximisation and minimisation, respectively [77]. These two goals are reflected in the normalised value of y_{ij} , where for benefit criteria:

$$y_{ij} = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})} \quad (26)$$

For the cost criteria:

$$y_{ij} = \frac{\max_i(x_{ij}) - x_{ij}}{\max_i(x_{ij}) - \min_i(x_{ij})} \quad (27)$$

where y_{ij} represents the evaluation value of the i -th alternative under the j -th criterion. This maps all values to a dimensionless scale of [0,1], where 1 always represents the optimal performance for that specific criterion.

• Equal weighting method [76]

As a baseline measure of unweighted performance, the equal weighting method distributes significance uniformly across all the n criteria:

$$\omega_j^{equal} = \frac{1}{n} \quad (28)$$

• Entropy weight method (EWM) [78]

The EWM approach computes the entropy value for each criterion using informational entropy, then assigns a weight for each criterion depending on the variation degree of every alternative [78]. First, the normalised values of the decision matrix are converted into a probability scaling P_{ij} :

$$P_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (29)$$

Next, the entropy E_j for each criterion is calculated [79]:

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^m P_{ij} \ln(P_{ij}) \quad (30)$$

Finally, the objective entropy weight for each criterion is derived from the degree of divergence [79]:

$$\omega_j^{EWM} = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)} \quad (31)$$

where the sum of all weights $\omega_j = 1$

• Criteria importance through intercriteria correlation (CRITIC) [80]

The CRITIC method assigns weights by evaluating both the standard deviation and the correlation among the 12 criteria [80]. Utilising the

same normalised matrix $\mathbf{Y} = [y_{ij}]$, the amount of information C_j is calculated [81]:

$$C_j = \sigma_j \sum_k^n (1 - r_{jk}) \quad (32)$$

where σ_j is the standard deviation of the j -th criterion, and r_{jk} is the linear correlation coefficient between the j -th and k -th criteria. The final weight is obtained via normalization [81]:

$$\omega_j^{CRITIC} = \frac{C_j}{\sum_{j=1}^n C_j} \quad (33)$$

• Method based on the removal effects of criteria (MEREC) [82]

Unlike variance-based methods, MEREC evaluates the influence of each criterion by measuring the degradation in overall performance when that criterion is removed [82]. MEREC operates on the raw matrix $\mathbf{DM}$ using a ratio transformation N_{ij} :

$$\text{For benefit criteria : } N_{ij} = \frac{\min_i(x_{ij})}{x_{ij}} \quad (34)$$

$$\text{For cost criteria : } N_{ij} = \frac{x_{ij}}{\max_i(x_{ij})} \quad (35)$$

The overall performance S_i of each alternative is computed using a logarithmic measure [83]:

$$S_i = \ln \left(1 + \frac{1}{n} \sum_{j=1}^n |\ln(N_{ij})| \right) \quad (36)$$

The performance is recalculated S'_{ij} with the j -th criterion removed. The total removal effect E_j and the final MEREC weights are given by [83]:

$$E_j = \sum_{i=1}^m |S'_{ij} - S_i| \quad (37)$$

$$\omega_j^{MEREC} = \frac{E_j}{\sum_{j=1}^n E_j} \quad (38)$$

• Analytic hierarchy process (AHP) [84]

The AHP derives weights based on expert pairwise comparisons of the predefined criteria organised into a $n \times n$ reciprocal matrix $\mathbf{C} = [c_{ij}]$, where n is the number of criteria. Saaty's scale is used to define the relative importance of criteria [84]. In this study, the pairwise judgements were provided by a panel of industrial and academic experts and aggregated into a single consensus judgement; the elicitation procedure and the construction of the final comparison matrix are detailed in Section 4.2 and Appendix 2.

The scaled comparison matrix $\mathbf{A} = [a_{ij}]$ is strictly positive and reciprocal. Each element a_{ij} represents the relative importance of criterion i -th compared to criterion j , it's established as follows [85, 86]:

$$a_{ij} = \frac{c_{ij}}{\sum_{i=1}^n c_{ij}} \quad (39)$$

with, $a_{ij} > 0$, $a_{ij} = \frac{1}{a_{ji}}$, $a_{ii} = 1$, for all $i, j = 1, 2, 3, \dots, n$. To extract the weight vector $\mathbf{W}^{AHP} = [\omega_1^{AHP}, \omega_2^{AHP}, \dots, \omega_n^{AHP}]^T$ in consistency with the AHP approach. The weights vector corresponds to the normalised right eigenvector associated with the maximum eigenvalue λ_{max} of matrix $\mathbf{A}$ [85,86]:

$$\mathbf{AW} = \lambda_{max} \mathbf{W} \quad (40)$$

Because human judgements inherently contain subjectivity, the mathematical validity of the weights must be verified using a consistency check. The consistency index (CI) is first calculated to measure the deviation from perfect consistency [85, 86]:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (41)$$

Subsequently, the consistency ratio (CR) is computed by dividing the CI by the random index of the matrix size n (RI), usually it corresponds to the average CI of an arbitrarily generated reciprocal matrix of the same order n [86]:

$$CR = \frac{CI}{RI} \quad (42)$$

A matrix is considered to have an acceptable level of logical consistency and thus the obtained weights vector values are deemed valid if $CR < 0.1$. If $CR \geq 0.10$, the comparison matrix C must be re-evaluated to eliminate contradictory comparisons.

• Stepwise weight assessment ratio analysis (SWARA) [87]

To mitigate the consistency challenges of large AHP matrices, SWARA elicits expert judgements sequentially. Criteria are ranked from most to least important [87]. The relative importance gap (s_j) dictates how much less important the j -th criterion is compared to the $(j-1)$ -th criterion. The coefficient k_j and recalculated weight q_j are defined as [88]:

$$k_j = \begin{cases} 1 & \text{if } j = 1 \\ s_j + 1 & \text{if } j > 1 \end{cases} \quad (43)$$

$$q_j = \begin{cases} 1 & \text{if } j = 1 \\ \frac{q_{j-1}}{k_j} & \text{if } j > 1 \end{cases} \quad (44)$$

The subjective weights are established by normalizing the intermediate values as follows [88]:

$$\omega_j^{SWARA} = \frac{q_j}{\sum_{j=1}^n q_j} \quad (45)$$

2.3.2. TOPSIS Ranking method [81]

Following the application of the distinct weight vectors, the TOPSIS algorithm is employed to identify the globally optimised BTMS configuration. It operates on the principle that the optimal design should have the smallest geometric distance to the Positive Ideal Solution (PIS) and the largest geometric distance to the Negative Ideal Solution (NIS) [89,90]. Firstly, the scaled decision matrix $Y = [y_{ij}]$ is normalised to eliminate the influence of differing units and to preserve the proportionality among values, as follows: $r_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^m y_{ij}^2}}$.

The weighted normalised decision matrix is then constructed by applying the weight obtained from each approach [81]: $v_{ij} = \omega_j \cdot r_{ij}$.

The PIS and NIS are defined as the highest and lowest values in each column of $V = [v_{ij}]$.
 $PIS = \{v_1^+, v_2^+, \dots, v_n^+\}$ where $v_j^+ = \max(v_{ij})$
 $NIS = \{v_1^-, v_2^-, \dots, v_n^-\}$ where $v_j^- = \min(v_{ij})$.

The Euclidean distance from each i -th configuration to the ideal solution is defined as [81]:

$$\begin{cases} D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \\ D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \end{cases} \quad (46)$$

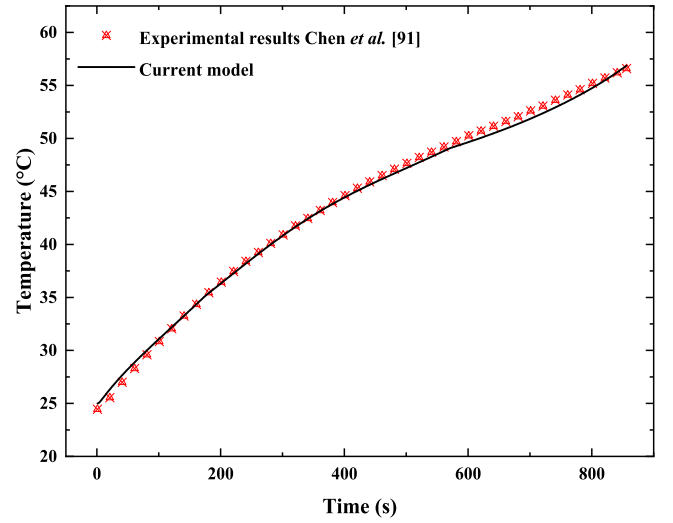
Finally, the relative closeness coefficient C_i is calculated to rank the overall performance of each configuration [81]:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (47)$$

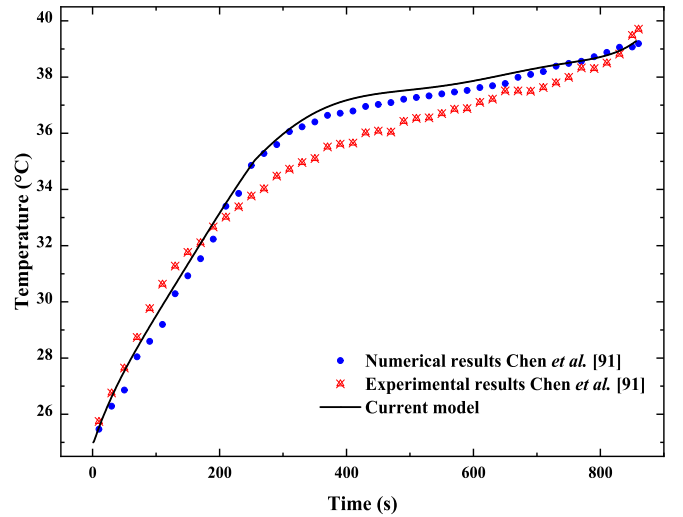
The C_i factor is in the range of 0 to 1, the configuration that yields the highest score represents the optimal design among all the scenarios.

3. Numerical validation

To validate the model for a single battery, the developed lumped thermal model was used to predict the temperature variation of a single cylindrical cell under controlled conditions (see Fig. 6(a)). The experimental benchmark Chen et al. [91] consists of measuring cell temperature during the discharge process under 4C rate, with an accuracy of $\pm 0.15^\circ\text{C}$ at an ambient temperature of 25°C . The developed model predicts the temperature of the cell with an error against the experimental results of 0.355°C for the mean absolute error (MAE) and 0.428°C for root mean square error (RMSE).



(a)

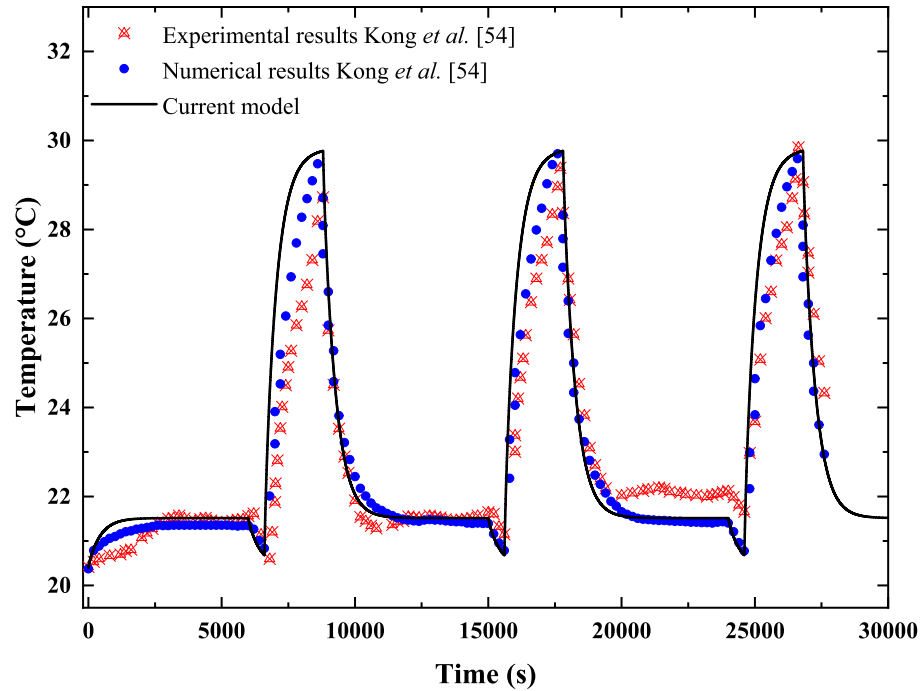


(b)

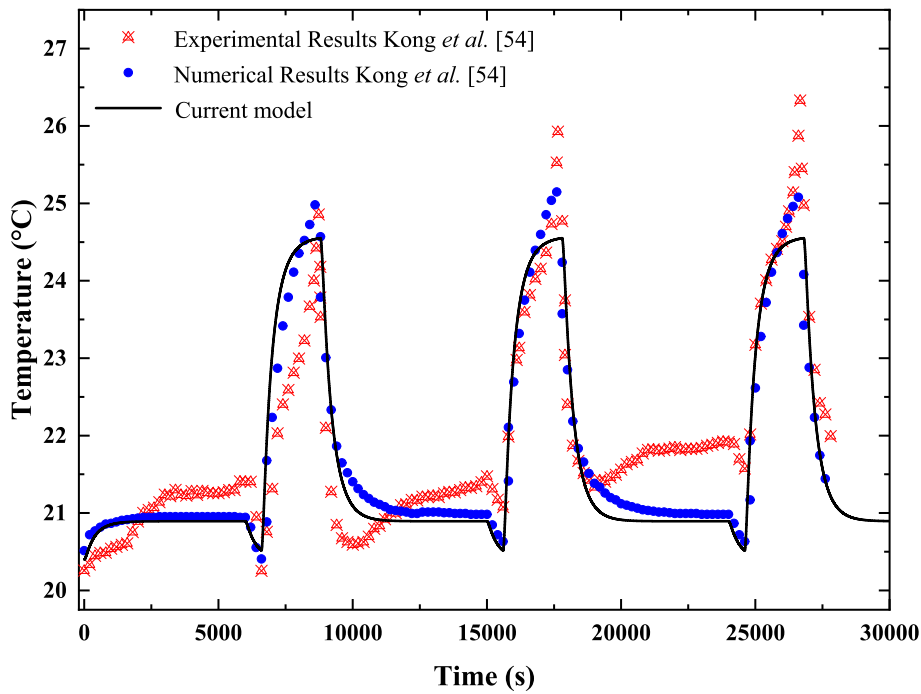
Fig. 6. Temperature benchmark of the cell during 4C discharge, (a) natural convection, (b) PCM-cooling.

The same cell was inserted into a container with a 2 mm gap to incorporate 9 g of melted PCM RT35H, then the cell was discharged at 4C rate [91]. The developed model predicts the temperature of cell in this configuration with good precision, reflected by an error value of 0.83 °C for MAE and 0.917 °C RMSE against the experimental data (see Fig. 6(b)).

To verify the accuracy and computational robustness of this hybrid model, a rigorous comparative analysis was executed against the experimental and CFD datasets reported by Kong et al. [54]. In the current validation scenario, a hybrid PCM-LC battery pack was maintained at a controlled ambient temperature of 20–22 °C. The system was subjected to three continuous charge-discharge cycles, separated by



(a)



(b)

Fig. 7. Comparison between, (a) the maximum and (b) the minimum temperature within the battery pack [54].

10 min rest periods. An asymmetric C-rates were applied with a high discharge rate of 1.5C and a standard charge rate of 0.5C. This dynamic cyclic loading tests the numerical ability of the model to simultaneously capture internal heat generation process, passive latent heat absorption, and active LC heat extraction.

As illustrated in Fig. 7, the simulated maximum and minimum battery surface temperatures exhibit agreement with both the experimental measurements and CFD predictions. The model accurately maps the transient temperature evolution across all three cycles. Minor discrepancies observed at the thermal peaks are primarily attributed to uncertainties regarding the precise PCM mass and boundary conditions reported in the original experimental setup. Furthermore, during the experiment, the LC temperature increased over time, which is attributed to the limited chiller capacity dedicated to the active system. Also, the 2 °C uncertainty in the ambient temperature further complicates the experimental replication. Nevertheless, despite these external experimental variances, the proposed 3D thermal network demonstrates accurate predictive results.

To assess the validation of the numerical model, the error metrics (Eqs. (48) and (49)) against both experimental and CFD results are provided. The MAE against the CFD results is 0.44 °C for the maximum and 0.189 °C for the minimum pack temperature, with a RMSE value of 0.779 °C and 0.253 °C, respectively. Against the experimental measurements the MAE is 0.86 °C for the maximum cell temperature and 0.53 °C for the minimum cell temperature, with RMSE values of 1.35 °C and 0.68 °C, respectively. The slightly larger experimental errors are consistent with the reported experimental uncertainties. These quantitative metrics confirm the model's physical suitability, justifying its application for the massive-scale parametric optimisation of hybrid BTMS under high-load conditions.

$$MAE = \frac{1}{N} \sum_{i=1}^N |T_{si} - T_{exp,i}| \quad (48)$$

Criteria name	T_{max}	ΔT_{max}	ED	δ	θ	γ	ξ	ϖ	ζ	ϕ	o	q
relative importance (s_j)	0	0.1	0.2	0	0.4	0	0	0	0	0	0	0

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (T_{si} - T_{exp,i})^2} \quad (49)$$

Regarding the uncertainty and repeatability of the validation, three complementary elements should be highlighted. First, the thermal network developed is fully deterministic: for identical inputs, repeated simulations return identical temperature fields, so that the numerical repeatability is exact, while the adaptive time step of Eq. (22) keeps the solution within its stability bound. The uncertainty of the comparison therefore originates mainly from the reference data and from the input parameters. Second, the deviations obtained are commensurate with the uncertainties of the references: the temperature measurement accuracy is ± 0.15 °C in [91], whereas an ambient temperature uncertainty of about 2 °C, a gradual drift of the coolant temperature and an uncertain PCM mass affect the dataset of [54]. Against the CFD predictions of [54], which are free from measurement noise, the MAE drops to 0.19–0.44 °C, confirming that a significant part of the deviation with respect to the experiments stems from experimental uncertainties rather than from the network model formulation. Third, the model was confronted with three datasets from two independent studies, covering different cooling modes (natural convection, passive PCM and hybrid PCM-LC), current rates (0.5C to 4C) and scales (single cell and battery module), including three

consecutive charge–discharge cycles without noticeable drift of the error from one cycle to the next (Fig. 7). The consistent error level across these independent benchmarks constitutes an indirect repeatability check of the predictive capability of the model. Finally, since the MCDM framework compares 78,000 configurations computed with the same model and assumptions, systematic modelling deviations shift the absolute temperatures of all designs in the same direction and cancel out in their relative ranking.

4. Results and discussion

4.1. Simulation cases

The LHS method was deployed to generate a set of the design spaces for the 7 design variables. To visualise the uniformity of this generated dataset, a scatter plot matrix was constructed (see Fig. 8). Within this matrix, each plot illustrates the relationships between two design variables, where a variable in a given column (x-axis) is plotted against the corresponding variable in row (y-axis). The 1000 generated sample points uniformly scatter across their predefined boundaries. Meanwhile, the conditioned variables a_1 and a_2 align strictly with the established rule-based control logic. This rigorous sampling ensures a comprehensive evaluation of the hybrid BTMS across a vast array of thermal and fluidic conditions.

4.2. Weight calculation

The subjective weighting process in AHP and SWARA requires human evaluation before the algorithm assigns weights; details of scoring methodology are provided in Appendix 2. In the current study the relative importance of 12 criteria and its ranking for the SWARA method are given as follows:

while for the AHP approach, the reciprocal matrix C is constructed from the Saaty scale importance vector by dividing the transposed vector by the corresponding criterion scaled value:

$$Coeff = \begin{bmatrix} \text{Criteria} & T_{max} & \Delta T_{max} & ED & \delta & \theta & \gamma & \xi & \varpi & \zeta & \phi & o & q \\ C_i & 9 & 8 & 3 & 3 & 3 & 3 & 3 & 2 & 1 & 3 & 1 & 1 \end{bmatrix}$$

$$C = [Coeff^T/C_1, Coeff^T/C_2, \dots, Coeff^T/C_{12}]$$

The importance vector $Coeff$ is the consensus vector of the expert panel described in Appendix 2. Since every element of C is the ratio of two consensus scores ($c_{ij} = C_i/C_j$), the matrix is perfectly consistent, its principal eigenvalue equals the number of criteria ($\lambda_{max} = n = 12$, hence $CI = CR = 0$ in Eqs. (41) and (42)), and the normalised principal eigenvector of Eq. (40) reduces to the normalised importance vector. This yields the AHP weights reported in Table 3. For readability, the same judgements are reported in Table 2-A (Appendix 2) after rounding each ratio to the nearest value of Saaty's discrete 1–9 scale. This rounding introduces only a marginal inconsistency ($\lambda_{max} = 12.021$, $CR = 0.0013 < 0.10$), and the eigenvector weights of the rounded matrix differ from those of Table 3 by less than 0.012 in absolute value, which does not affect the conclusions drawn from the AHP-based ranking.

The weight distributions derived from the six employed methods are

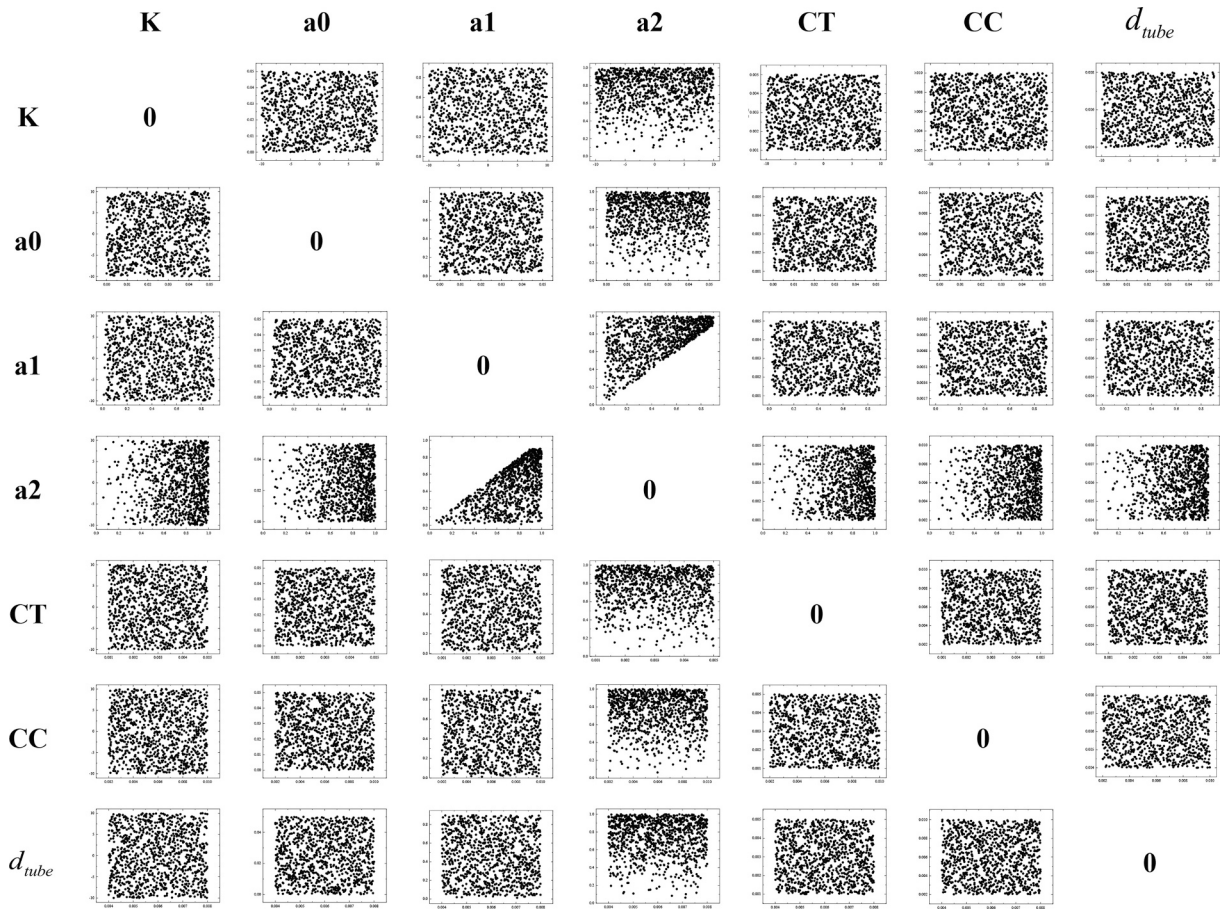


Fig. 8. LHS sampling data diagram.

Table 3
Assigned weights values of different methods.

Criterion	Equal	EWM	CRITIC	MEREC	AHP	SWARA
$T_{\max}$	1/12	0.018	0.060	0.072	0.225	0.129
$\Delta T_{\max}$	1/12	0.008	0.048	0.195	0.200	0.117
Energy density (ED)	1/12	0.030	0.050	0.074	0.075	0.098
Mass ratio (δ)	1/12	0.013	0.034	0.037	0.075	0.098
Thermal stability (θ)	1/12	0.078	0.089	0.045	0.075	0.070
Super cooling (γ)	1/12	0.084	0.082	0.055	0.075	0.070
Corrosiveness (ξ)	1/12	0.062	0.085	0.165	0.075	0.070
Toxicity (ϖ)	1/12	0.087	0.064	0.040	0.050	0.070
Flammability (ζ)	1/12	0.254	0.173	0.150	0.025	0.070
Cost (ϕ)	1/12	0.060	0.115	0.043	0.075	0.070
Environment ($\circ$)	1/12	0.252	0.121	0.075	0.025	0.070
Recyclability (ϱ)	1/12	0.054	0.079	0.050	0.025	0.070

presented in Table 3. As anticipated, the objective and subjective methods yield different weight allocations due to their distinct mathematical formulas. In the EWM approach, weights are dictated by the degree of data dispersion. Consequently, the highest weights are allocated to ζ (0.254) and $\circ$ (0.252), which exhibit the largest numerical variance across the criteria dataset. Conversely, the four quantitative indicators combined receive a marginal total weight of only 0.069, with the minimum value of 0.008 assigned to $\Delta T_{\max}$. The CRITIC method tackles the weakness of EWM by incorporating both standard deviation and inter-criteria correlation, assigning lower weights to criteria that are correlated with others to mitigate unnecessary repetition. The MEREC algorithm imposes an additional limit on the range of weight allowance between qualitative and quantitative criteria. It evaluates the importance through the effect of eliminating each criterion, and the absence of

any criterion causes the overall performance of the alternatives to decrease in a uniform way. In contrast, the subjective methods determine the weights only based on expert opinion. In the engineering design of a BTMS for EVs, the emphasis is on thermal performance rather than qualitative indicators.

4.3. Ranking results

The optimal results according to the TOPSIS ranking method are listed in the Table 4, where the optimal case for each weight method is listed, along with two optimal scenarios (optimal $T_{\max}$, optimal $\Delta T_{\max}$) taking $T_{\max}$ and $\Delta T_{\max}$ as the sole criterion respectively.

In Table 4, the results show that 6 optimal hybrid BTMS designs were selected. SWARA and Equal settle for the same optimal scenario, similarly CRITIC and MEREC appoint an identical case as the optimal. These similitudes can be traced to the weight value assigned in Table 3. The mentioned methods assign comparable weight values, especially between SWARA and Equal for the qualitative PCM criteria.

It's worth mentioning that in all the optimal BTMS scenarios the C_1 LC arrangement is chosen. This coherent agreement on one configuration proves its advantageous thermal performance compared to the other two arrangements. Further analysis of the ranking results sorts the LC configuration as follows $C_1 > C_2 > C_0$. In the C_0 configuration, the LC absorbs heat along the flow path, developing a progressive decrease in the temperature differential between the PCM and the coolant. This leads to a localised hotspot at the outlet face of the battery pack. The C_1 configuration effectively neutralises these hotspots by inducing a counter-current flow in the middle tube layer. By aligning the cold inlet of the middle layer with the warmer downstream LC in the top and bottom layers. While the staggered C_2 configuration successfully

Table 4

Comparison of the optimal BTMS designs.

	Optimal $T_{\max}$	Optimal $\Delta T_{\max}$	Optimal Equal	Optimal EWM	Optimal CRITIC	Optimal MEREC	Optimal AHP	Optimal SWARA
PCM	OP35E	SP29 eu	A28	SP29 eu	A28	A28	RT28 HC	A28
LC configuration	C ₁	C ₁	C ₁	C ₁	C ₁	C ₁	C ₁	C ₁
K (°C)	−9.67	2.89	2.92	−1.09	2.69	2.69	2.46	2.92
a_0	0.046	$4.29 \cdot 10^{-4}$	0.002	0.025	0.029	0.029	0.025	0.002
a_1	0.778	0.608	0.606	0.539	0.480	0.480	0.466	0.606
a_2	0.868	0.761	0.788	0.733	0.917	0.917	0.746	0.788
CT (mm)	3	3.44	2.51	1.27	1.89	1.89	2.43	2.51
CC (mm)	8.56	2.57	4.85	2.23	7.64	7.64	5.34	4.85
d_{tube} (mm)	7.48	4.63	5.72	4.06	5.48	5.48	5.63	5.72
$T_{\max}$ (°C)	26.91	31.59	31.8	31.43	31.55	31.55	31.28	31.8
$\Delta T_{\max}$ (°C)	2.108	0.054	0.329	1.141	0.182	0.182	0.178	0.329
ED (kWh/m ³)	193.39	255.43	239.19	303.97	226.77	226.77	236.64	239.19
Mass ratio	0.694	0.589	0.710	0.671	0.691	0.691	0.697	0.710

Table 5

Best ranked PCMs.

PCM name	Liquid density (kg/m ³)	Solid density (kg/m ³)	Solid heat capacity (kJ/(kg·K))	Liquid heat capacity (kJ/(kg·K))	Thermal conductivity (W/(m·K))	Latent heat (kJ/kg)	Solidus temperature (°C)	Liquidus temperature (°C)
OP35E	580	580	2.9	2.9	3.7	168	31.2	35.2
RT28 HC	825	825	2	2	0.2	250	27	29
A28	789	789	2.22	2.22	0.21	265	26	30
SP29 eu	1500	1600	2	2	0.5	200	27	30

disrupts vertical hotspot alignment by horizontally displacing the middle cooling tube, it retains the co-current flow direction across all three layers. Consequently, C₂ still suffers from small longitudinal thermal degradation. In terms of PCM selection, four were listed among the 8 best ranked cases, OP35E (Hangzhou Ruhr Tech Co., Ltd.) [92], SP29 eu (RUBITHERM) [93], A28 (PCMproducts) [94], and RT28 HC (RUBITHERM) [95]. A28 was selected in 4 optimal cases, due to its superior thermal characteristics namely latent heat. The SP29 eu is the only inorganic PCM, whereas the others are organic ones, see Table 5.

Analysing the 6 ranked designs individually reveals that in the case of the optimal $T_{\max}$, the maximum temperature registered is 26.91 °C, which is much lower compared to the other cases. This phenomenon is mainly due to the LC effect, where the inlet temperature is set to $T_{inlet} = 15.33$ °C. Also, the large diameter of the tube and high velocity dampen the heat generated from the cells. Furthermore, the OP35E possesses high thermal conductivity, enabling fast heat transfer between

the cells and LC. The other optimal cases display comparable thermal performance and design variable values. These performance similarities indicate that the optimal hybrid BTMS design case can be identified in a confined range of design variable values. Aside from the optimal $T_{\max}$ and EWM designs, the other ones employ an LC inlet temperature of 27.46 °C – 27.92 °C. In this range, the PCM is already in a phase transition zone; the passive absorption of the generated heat provides a homogenous temperature across the battery pack. Similarly, the rule-based coefficient for LC is set in a quite confined range, with the exception of the a_2 coefficient for MEREC and CRITIC, which settle for a high value of 0.917. Furthermore, the geometrical parameters of the battery pack, such as CC and CT, exhibit large value discrepancies. Nevertheless, the thermal performance listed is quite similar and within an acceptable range for a functioning BTMS.

The temporal evolution of $T_{\max}$ for the 6 weighting approaches is plotted in Fig. 9, it shows that the thermal performances of all BTMS designs are comparable, with a notable temperature difference during the last charging cycle. The optimal EWM design involves a low inlet LC temperature, facilitating the removal of the excessive heat of the cells from the pack. In contrast, the inlet LC temperature employed in Equal/SWARA and CRITIC/MEREC is above 27 °C, which is already in the phase transition range of A28, meaning a portion of the latent heat is inoperative. Consequently, restraining temperature spikes is weakened, which explains the temperature peaks during the last charging cycle.

4.4. Comparison of whole ranks

As presented in Table 4, the criteria weighting methodology directly

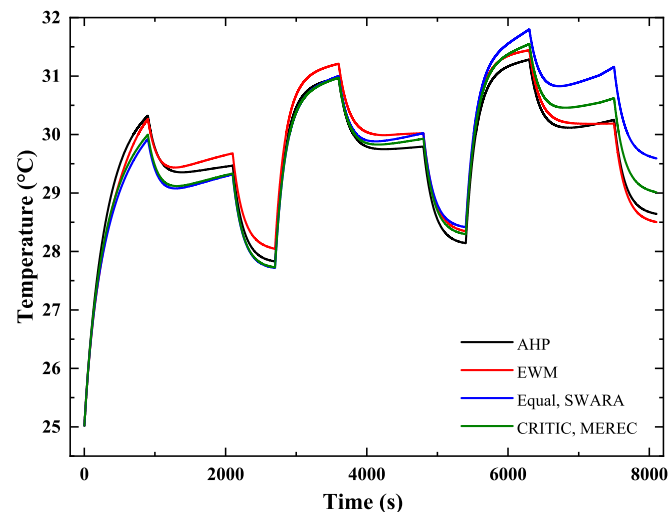


Fig. 9. Time evolution of the maximum temperature of the cell ($T_{\max}$) for the optimal designs.

Table 6

Spearman correlation between the ranking of the hybrid BTMS design.

	Equal	EWM	CRITIC	MEREC	AHP	SWARA
EQUAL	1	−0.555	0.468	0.896	0.751	0.931
EWM	−0.555	1	0.05	−0.247	−0.079	−0.317
CRITIC	0.468	0.05	1	0.613	0.669	0.587
MEREC	0.896	−0.247	0.613	1	0.948	0.988
AHP	0.751	−0.079	0.669	0.948	1	0.927
SWARA	0.931	−0.317	0.587	0.988	0.927	1

influences the optimisation outcomes for the hybrid BTMS. This discrepancy produces an ambiguity regarding the reliability of the selection process. To mathematically assess the consistency of the weighting approach in ranking the whole 78,000 simulated cases, a Spearman correlation analysis was conducted. Since TOPSIS optimisation results consist of discrete rank positions, the Spearman correlation coefficient (SCC) serves as an ideal non-parametric metric for evaluating the monotonic relationship across all six weighting approaches [96,97].

The comparison of SCC for every pair of the weighting approaches is presented in Table 6. The SCC reflects the connection between two ranking results; its value ranges from -1 to 1 , with a value of 0 indicating an inconsistent relationship. The SCC in Table 6 reveals a strong correlation between MEREC, AHP and SWARA ($\text{SCC} > 0.9$); in other words, these three methods yield nearly identical ranking patterns for the hybrid BTMS design. Moreover, the equal weight method produces a resemblant ranking to SWARA and MEREC and a less similar degree to AHP. EWM exhibits a negative SCC with 4 methods, indicating that the methods prioritise different criteria during ranking, which is rooted in the weight distribution. CRITIC exhibits moderate rank alignment with the other methods, apart from EWM, where the value of the SCC is 0.05 .

4.5. Optimised BTMS performance under extreme conditions

The proposed MCDM framework identified the optimal hybrid configurations under standard ambient temperature $T_{\text{amb}} = 25^\circ\text{C}$, real-

world EVs are subjected to a broader range of environmental and electrical stresses. To evaluate the capabilities of the four optimal BTMS cases, a comprehensive analysis was conducted under hot climates and different charging/ discharging profiles. While 45°C serves as the safety limit, 35°C is employed in this study as a performance threshold to evaluate the optimised BTMS configurations under extreme loads.

4.5.1. Effect of ambient temperature

The four optimal BTMS designs were evaluated under two extreme ambient temperatures of 35°C and 45°C . In these scenarios the PCMs employed were pre-melted as the temperature exceeded the liquidus threshold. Hence, the BTMS relies entirely on the active LC network to extract heat from the battery pack.

Figs. 10(a) and 10(b) depict the time evolution of T_{max} and ΔT_{max} for the battery pack under the same current profile used earlier. Throughout the three cycles the optimal BTMS designs exhibit similar thermal behaviour, with the notable exception of the EWM optimal configuration, which provides lower temperature compared to the other three. Under a temperature of $T_{\text{amb}} = 35^\circ\text{C}$, the EWM BTMS configuration keeps the battery pack's temperature within the optimal operating range for most of the cycling time. In contrast, the other three designs struggle to adequately dissipate the heat under extended cycling loads. For the SWARA/Equal, AHP, MEREC/CRITIC, and EWM, T_{max} surpasses the 35°C threshold for 68.6%, 50.8%, 42.7%, and 15.2% of the total operating time, respectively. Despite these large variations in T_{max} , all four

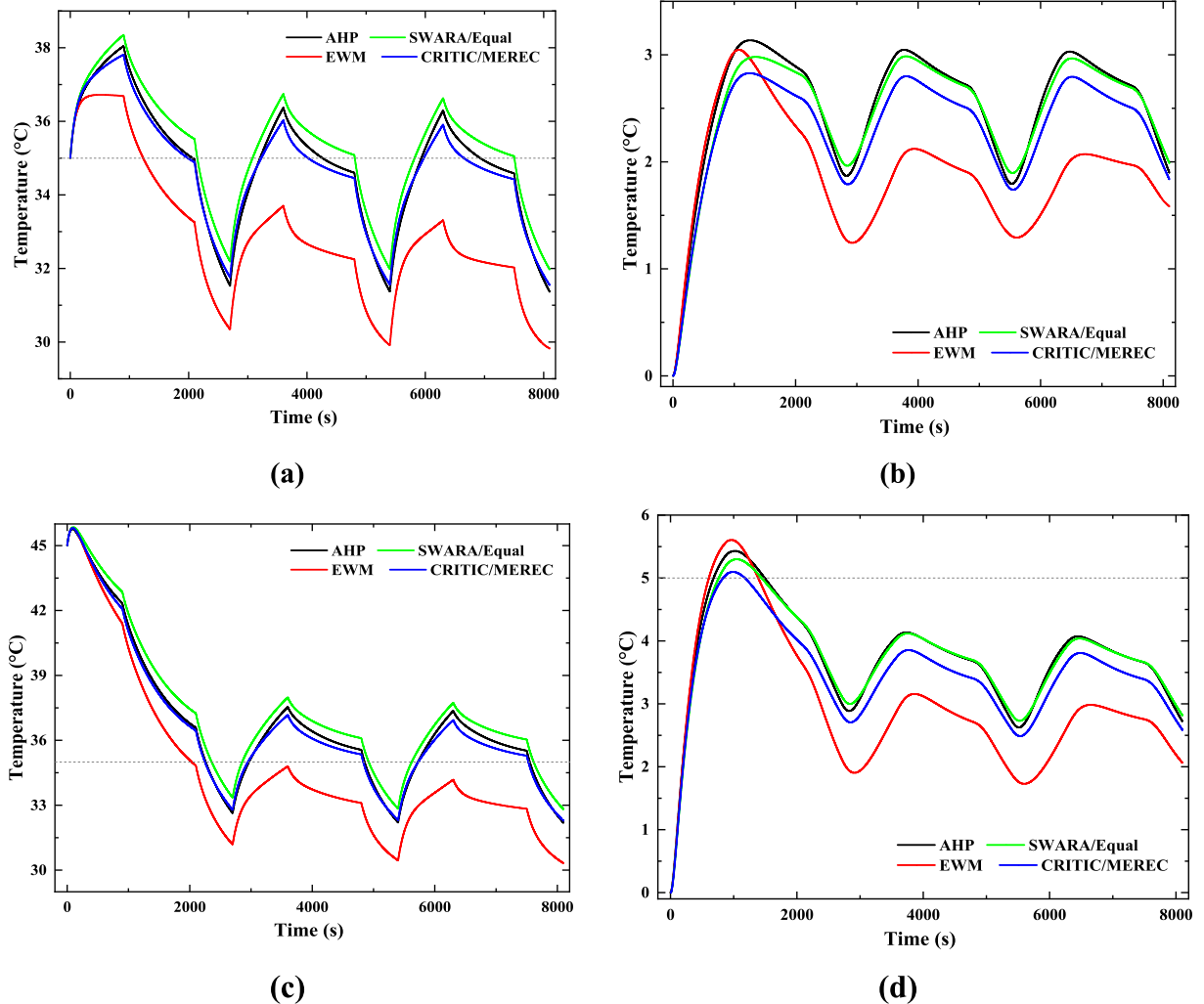


Fig. 10. T_{max} ($^\circ\text{C}$) and ΔT_{max} ($^\circ\text{C}$) time evolution under (a-b) $T_{\text{amb}} = 35^\circ\text{C}$, (c-d) $T_{\text{amb}} = 45^\circ\text{C}$.

optimal BTMS configurations successfully restrict localised hotspots, maintaining a uniform maximum thermal gradient $\Delta T_{\max}$ below 3.1°C throughout the entirety of the cycles.

Moreover, the thermal response under the $T_{\text{amb}} = 45^\circ\text{C}$ ambient condition (Figs. 10(c) and 10(d)) presents an extreme hot climate stress test. In the first charge-discharge cycle, the active LC network demonstrates a profound cooling performance, where the temperature of the battery pack decreases continuously. In the final two cycles, the thermal profile fluctuates between 30°C and 38°C (see Fig. 10(c)). Under these extreme environmental conditions, only the EWM-optimised BTMS configuration keeps the battery pack below the 35°C threshold for most of the cycling time. Conversely, the remaining three designs expose the battery pack to elevated temperatures for extended periods, inevitably accelerating capacity degradation and increasing safety risks. Quantitatively, the battery pack temperature exceeds the 35°C threshold for 79.1%, 73.7%, 73.1%, and 25.1% of the total cycling duration for the SWARA/Equal, AHP, MEREC/CRITIC, and EWM BTMS configurations, respectively. The initial temperature condition combined with an inlet LC temperature smaller than 28°C generates a temporary thermal shock, resulting in a high $\Delta T_{\max}$ spike of 5.6°C during the first cycle (see Fig. 10(d)). However, the active LC network rapidly stabilises the gradient in the following cycles.

The superior performance of the EWM-optimised configuration under $T_{\text{amb}} = 45^\circ\text{C}$ is governed by the transition from latent to sensible heat transfer. Under high ambient temperature, the PCMs in all con-

figurations are fully pre-melted, rendering their latent heat capacity inoperative. Consequently, the thermal buffering relies only on the sensible heat capacity and thermal conductivity of the liquid-state PCM. The SWARA and AHP designs employ organic PCMs (A28 and RT28 HC) which possess low thermal conductivities ($\lambda_{\text{PCM}} \approx 0.21 \text{ W/m}\cdot\text{K}$). This led to heat accumulation at the cell surface faster than it can diffuse through the liquid PCM to reach the LC. Conversely, the EWM design employs the inorganic SP29 eu PCM, which possesses high thermal conductivity ($\lambda_{\text{PCM}} = 0.5 \text{ W/m}\cdot\text{K}$) and a lower LC inlet temperature. This establishes a thermal gradient that strengthens heat extraction from the battery pack, preventing thermal accumulation and successfully restraining $T_{\max}$ below the other designs.

Cycling the battery pack under hot climates underscores the necessity of choosing adequate PCM to the ambient temperature. Despite this limitation, the active LC network prevented heat accumulation and temperature increasing across the different BTMS proposed. The EWM-optimised configuration proved its superior thermal performance by restricting the battery pack temperature below the 35°C threshold for long periods. The results confirm that the hybrid BTMS is more versatile for a wide range of ambient temperatures, and its performance can be optimised for a large set of surrounding conditions.

4.5.2. Effect of electrical loads

In addition to environmental effects, BTMSs must also handle different quantities of internal heat generation induced by varying

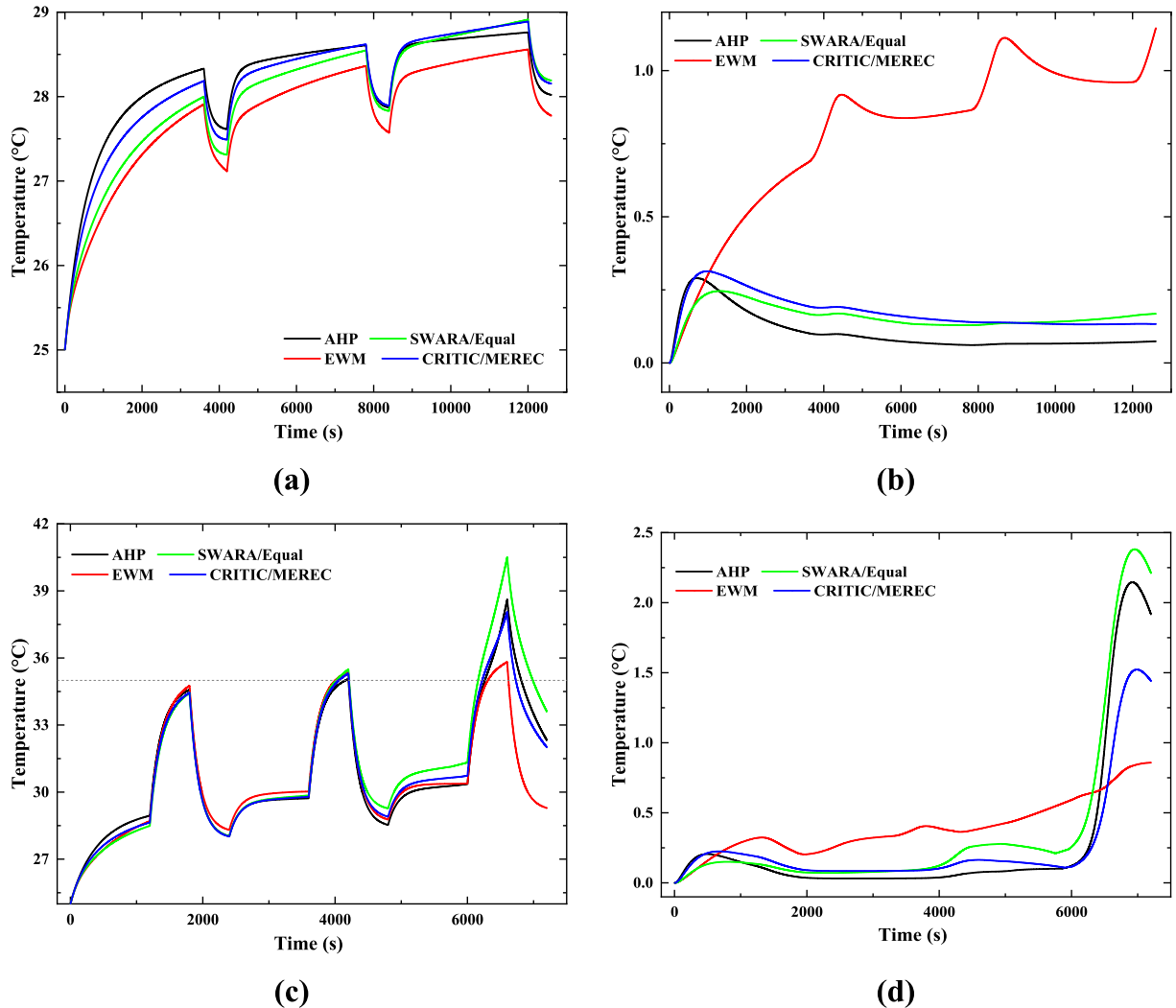


Fig. 11. $T_{\max}$ ($^\circ\text{C}$) and $\Delta T_{\max}$ ($^\circ\text{C}$) time evolution under (a-b) 2C charge 2C discharge current, (c-d) 6C charge 3C discharge current.

charging and discharging conditions. The optimal BTMS designs were tested under two distinct charging/discharging profiles. First, a symmetric moderate load (2C charge / 2C discharge) and an extreme asymmetric fast-charging load (6C charge / 3C discharge), which assess the BTMS beyond the current profile employed in the evaluation.

Under the moderate 2C/2C profile (Figs. 11(a) and 11(b)), $T_{\max}$ remains below 29 °C and $\Delta T_{\max}$ below about 1.2 °C for all four optimal designs throughout the three cycles, the PCM buffering most of the generated heat. Under the extreme 6C/3C profile, during the first discharge phase, $T_{\max}$ rises gradually and remains below 29 °C, demonstrating the effective thermal buffering of the PCM (see Fig. 11(c)). Under the extreme charging load, the temperature spikes sharply just below the 35 °C critical threshold (see Fig. 11(c)). It then decreases during the relaxation period, stabilising below 29 °C. The second cycle exhibits a similar thermal profile, although $T_{\max}$ breaches the 35 °C threshold by the end of the charging phase. Critically, during the second relaxation phase, the PCM is not completely regenerated as in the previous cycle. A notable discrepancy in $T_{\max}$ appears between the EWM and SWARA/Equal optimised cases by the end of the last discharge. The final charging period exposes a difference in thermal management among the four configurations. $T_{\max}$ reaches 40.5 °C in the SWARA/Equal design, whereas it is constrained to 38 °C in the AHP and MEREC/CRITIC cases, and successfully limited to a peak of only 35.8 °C in the EWM configuration. Regarding spatial temperature distribution, the battery pack temperature remains homogeneous throughout the cycling process. During the final charging cycle, $\Delta T_{\max}$ rises sharply from 0.5 °C to exceed 2.3 °C in the SWARA/Equal design. However, these values are within the safe operational window for lithium-ion battery packs as seen in Fig. 11(d).

During fast charging, the internal irreversible heat generation is violent. In the SWARA/Equal optimised designs, the liquid coolant inlet temperature is configured very high ($T_{\text{inlet}} \approx 27.9^\circ\text{C}$), which is near the nominal melting temperature of the A28 PCM (28 °C, within its 26–30 °C phase-change range). Consequently, during the brief 10 min relaxation periods, the LC couldn't re-solidify the PCM. When the subsequent charge cycle initiates, the PCM is already in transition or liquid state. The BTMS is overwhelmed by the heat flux generated during high load cycling, resulting in temperature spikes up to 40.5 °C. In contrast, the EWM configuration provides a much colder LC inlet, which allows almost a complete solidification of the inorganic PCM during the resting phases. The EWM configuration absorbs the abrupt heat generation of the cells during successive fast-charging cycles.

The performance of the EWM design is driven by two mechanisms. First, its lower LC inlet temperature allows the active system to rapidly extract excessive heat from the battery pack. Second, the inorganic SP29 eu possesses a higher thermal conductivity than the organic PCMs employed in the other cases. Conversely, in the SWARA/Equal optimised designs, the LC flow velocity drops to a small value when the pack temperature falls below 30 °C, as reflected by the coefficient a_0 . Consequently, the solidification process of the A28 PCM is slower than the other configurations.

4.6. Limitations

While the proposed 3D lumped thermal network provides time-efficient framework for MCDM optimisation, the physical simplifications required to build the model introduce a few limitations that should be acknowledged.

First, the model assumes that heat transfer within the liquid phase of the PCM occurs purely via conduction. In reality, as the PCM melts, buoyancy-driven fluid motion can enhance the effective heat transfer rate. However, because the PCM in this hybrid BTMS is tightly confined within the narrow interstitial voids between the cylindrical cells and the cooling tubes, the characteristic length of the fluid domains is extremely small. This spatial restriction strongly limits the Rayleigh number, and hence the development of natural convection, in most of the PCM

domain [98]. Nonetheless, neglecting this phenomenon yields a slightly conservative prediction of the liquid-state cooling performance of BTMS. To quantify this assumption, a scale analysis based on the Rayleigh number, $Ra = g\beta\Delta T \cdot L^3 / (\nu\alpha)$, was performed with representative properties of liquid organic PCMs ($\beta \approx 10^{-3} \text{ K}^{-1}$, $\nu \approx 5 \times 10^{-6} \text{ m}^2/\text{s}$, $\alpha \approx 10^{-7} \text{ m}^2/\text{s}$), where L is the width of the liquid PCM layer and $\Delta T = 5 \text{ K}$ is adopted as an upper bound of the temperature difference across it. Two characteristic lengths must be distinguished. Along the x-axis between the cells to the LC tubes (CT), $1.27 \text{ mm} < L_{\text{CT}} < 3.44 \text{ mm}$ for the optimal designs (see Table 4), Ra_{CT} ranges from about 2×10^2 to 4×10^3 and reaches 1.2×10^4 at the upper bound of the design space ($L_{\text{CT}} = 5 \text{ mm}$). These values lie around the classical threshold ($Ra \approx 10^3$) below which heat transfer across a vertical liquid layer remains essentially conductive. The widest PCM layer is found along y-axis between two adjacent cells (CC), whose spacing reaches at most about 8 mm in practice. This gap gives $Ra_{\text{CC}} \approx 5 \times 10^4$ under the same temperature upper-bound ΔT , so that buoyancy-driven motion cannot be excluded there once the PCM is fully molten. Several features of the studied architecture nevertheless limit this effect. First, the PCM is crossed by the three layers of cooling tubes, spaced 17.5 mm along z-axis. These distributed cold surfaces continuously extract heat from the PCM, which limits its superheating and hence the effective ΔT entering Ra , and they divide the liquid column into short sub-domains, which hinders the development of a single convective vortex over the full cell height. Second, the two vertical walls of the cell-to-cell spacing are neighbouring cells at nearly identical temperatures ($\Delta T_{\max} \leq 0.33 \text{ K}$ for 5 of the 6 optimal designs, Table 4), so that no significant net temperature difference is imposed across this gap, any recirculation there remains localised within the inter-cell region and contributes little to the net heat transfer towards the cooling tubes. Finally, convection can only develop in fully molten PCM, since the solid fraction of the mushy zone strongly damps the flow, this fully liquid state is mainly reached under the extreme ambient conditions, where the PCM is pre-melted.

Second, aside from the apparent heat capacity during phase transition, the thermophysical properties of the PCMs and battery cells are given as temperature-independent constants. While these properties do exhibit mild temperature dependencies in real-world materials, locking them as constants was a deliberate simplification. It prevents the need to update their values at every iteration, thereby guaranteeing the speed of the proposed 3D model [56]. Quantitatively, over the 20–40 °C range, the heat capacity and the thermal conductivities of Li-ion cells vary by less than 4% and 5.7%, respectively [56]. Since the nodal temperatures of the network respond almost proportionally to the capacitances and conductances, the resulting deviation of the predicted temperature rise is of the same relative order. Moreover, the internal resistance, which is the most temperature-sensitive parameter since it controls heat generation, is already expressed as a function of the cell temperature (Eq. (3)), while the PCM properties are updated according to the phase state and liquid fraction.

Finally, the numerical formulation employs a single, symmetrical function to describe the apparent heat capacity of the PCM during both melting and solidification. Consequently, the thermal hysteresis is not considered, the current model may overestimate the rapidity with which the PCM regenerates [99]. Future study should consider asymmetric melting and solidification curves to capture thermal hysteresis to better predict the effect of the PCM on BTMS performance during continuous cyclic loading.

The influence of neglecting the reversible heat was bounded using the contribution reported by Chen et al. [60] for a similar cell (below 5% of the total heat generation above 1C). In the nominal case, this corresponds to a deviation lower than about 0.3 °C on $T_{\max}$, and lower than 0.8 °C for the most severe loading case ($T_{\max} = 40.5^\circ\text{C}$, Fig. 11), knowing that the sign alternation of the entropic heat between charge and discharge further reduces its cumulative effect. All the estimated deviations remain within the error level obtained during validation (RMSE of 0.43–1.35 °C against the experimental data). Moreover, they

act systematically on all the simulated configurations, since the MCDM framework ranks the BTMS designs relative to each other, these assumptions shift the absolute temperatures but are not expected to modify the ranking of the optimal BTMS designs.

5. Conclusion

In this study, an MCDM optimisation framework for a hybrid PCM-LC BTMS is implemented by employing a detailed 3D thermal network model, rather than more conventional optimisation approaches such as CFD or surrogate models. Despite the stated limitations, the model was validated against diverse experimental and CFD benchmarks, it maintains a reliable temperature estimation for wide range of operating conditions. Consequently, this framework enabled the evaluation of seven design variables across 78,000 distinct hybrid BTMS design configurations. To assess these designs, four quantitative and eight qualitative PCM criteria were considered. The analysis reveals that the C₁ LC configuration consistently outperformed C₂ and C₀ arrangements by effectively damping heat generation and mitigating localised hotspots. Among the 26 evaluated PCMs, organic A28 emerged as the optimal candidate for absorbing abrupt heat spikes during high C-rate cycling under the given conditions. Furthermore, the study revealed that the optimal BTMS is strongly linked to the initial optimisation objectives. The choice of criteria weighting strongly dictated the optimisation outcomes, subjective methods were designed to prioritise the thermal performance of the BTMS. Objective methods were highly sensitive to the numerical variance of qualitative criteria for the PCMs, including flammability and environmental impact. Spearman rank correlation analysis mathematically verified and highlighted the homogenous ranking of the BTMS design. Specifically, the analysis revealed a remarkably strong rank alignment (SCC > 0.9) among the MEREC, AHP, and SWARA weighting methods, confirming the statistical consistency of the optimal design selection profile.

Appendix A. Appendix 1

Qualitative criteria evaluation through Saaty scoring.

To assign scores for the qualitative criteria of the 26 PCMs evaluated in this study. First, the PCMs were initially classified into organic, inorganic, and biobased categories. In the literature, each group exhibits advantages and drawbacks, which serve as the baseline for qualitative assessment. The specific criteria are defined as follows:

Thermal Stability (θ): Defined as the ability of a PCM to maintain its thermophysical properties after undergoing multiple melting and solidification cycles [100].

Supercooling (γ): Refers to the phenomenon where a PCM remains in a liquid state below its melting point. This instability is significantly more pronounced in inorganic PCMs compared to organic and bio-based alternatives [101].

Corrosiveness (ξ): Characterizes the chemical reactivity of the PCM with its environment. Generally, inorganic PCMs exhibit high corrosiveness, whereas organic and biobased PCMs are relatively inert [102].

Toxicity (ϖ): Encompasses hazardous effects on human health and the ecosystem. Bio-based PCMs are broadly considered safe, and organic PCMs are safe under normal conditions. Conversely, inorganic PCMs often pose safety risks, where direct skin contact can cause irritation [101].

Flammability (ζ): Non-paraffin organic PCMs generally exhibit higher flammability than paraffins and must not be exposed to extreme temperatures or oxidizing agents. Inorganic PCMs inherently possess a very low flammability tendency [100].

Cost (ϕ): Reflects the abundance of raw materials, availability, and processing expenses. Commercial-grade organic PCMs are relatively inexpensive (approximately \$1.88–\$5.50/kg) [103]. While raw bio-based materials are cheap (palm kernel oil at \$1.32/kg, coconut oil at \$1.95–\$2.00/kg), commercial-grade bio-based PCMs can reach up to \$11.00/kg [104]. Inorganic PCMs remain highly affordable, ranging from \$3.08 to \$4.95/kg [103].

Environment (σ): Organic PCMs impose a higher environmental impact due to their fossil fuel origins and synthesis processes. A comparative life cycle assessment indicates that bio-based PCMs possess the lowest environmental footprint, followed by inorganic [104].

Recyclability (q): Indicates the ease of end-of-life processing to lower the overall environmental footprint. Organic and bio-based PCMs are generally easy to recycle, whereas inorganic PCMs require complex, dedicated consideration during recycling [105].

Following the categorisation, previously established Saaty scores from comparable MCDM literature [69–73] were utilised as foundational anchoring values for the respective PCM groups, ensuring consistency with widely accepted evaluations in the literature.

Finally, within each specific PCM type, the baseline scores were adjusted using data specifications provided by the manufacturers (Hangzhou Ruhr Tech Co., Ltd. [92], RUBITHERM (SP series [93] and RT series [95]), and PCMproducts [94]).

The principal findings of this optimisation process of hybrid BTMS are summarised as follows:

- The C₁ LC configuration consistently outperformed C₂ and C₀, for T_{max} and ΔT_{max} metrics.
- Organic PCM A28 was selected in four of the six optimal scenarios, combining a latent heat of 265 kJ/kg with a 26–30 °C phase-transition window.
- Spearman correlation coefficients above 0.9 confirmed the consistency of the MEREC, AHP and SWARA ranking schemes.
- Under hot climate conditions (T_{amb} = 35 °C and T_{amb} = 45 °C), the EWM-optimised configuration performed best, limiting the time above the 35 °C design threshold to 15.2% and 25.1% of the cycling time, respectively, against 42.7–79.1% for the other designs.

Ultimately, this novel approach provides a highly reliable and scalable MCDM framework for global BTMS optimisation. The proposed 3D thermal network strikes a balance between predictive accuracy and low computational cost, successfully capturing the transient, spatiotemporal temperature evolution of a battery pack under dynamic loads.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 945416.

Table 1-A
Commercial PCM studied.

PCM name	Liquid density (kg/m ³)	Solid density (kg/m ³)	Solid heat capacity (kJ/(kg·K))	Liquid heat capacity (kJ/(kg·K))	Thermal conductivity (W/(m·K))	Latent heat (kJ/kg)	Solidus temperature (°C)	Liquidus temperature (°C)	Melting temperature (°C)	Thermal stability (θ)	Supercooling (γ)	Corrosiveness (ξ)	Toxicity (π)	Flammability (ζ)	Cost (ϕ)	Environment (α)	Recyclability (ϱ)
Organic PCM																	
RT35 HC	770	880	2	2	0.2	240	34	36	35	6	2	1	3	8	4	8	7
RT31	760	820	2	2	0.2	165	27	33	30	6	2	1	3	8	4	8	7
RT28 HC	825	825	2	2	0.2	250	27	29	28	6	2	1	3	8	4	8	7
RT35	770	860	2	2	0.2	165	32	38	35	6	2	1	3	8	4	8	7
OP35E	580	580	2.9	2.9	3.7	168	31.2	35.2	33.2	6	3	1	3	8	4	8	7
n-Octadecane	777	880	3.25	2.6	0.149	236.09	27.85	32.85	30.35	6	3	1	3	8	4	8	7
A28	789	789	2.22	2.22	0.21	265	26	30	28	6	3	1	3	7	4	8	7
A29	785	785	2.22	2.22	0.21	230	27	31	29	6	3	1	3	7	4	8	7
A30	790	790	2.22	2.22	0.21	230	28	32	30	6	3	1	3	7	4	8	7
A31	790	790	2.22	2.22	0.21	230	29	33	31	6	3	1	3	7	4	8	7
A32	845	845	2.2	2.2	0.21	120	30	34	32	6	3	1	3	7	4	8	7
A33	790	790	2.22	2.22	0.21	230	31	35	33	6	3	1	3	7	4	8	7
A34	790	790	2.22	2.22	0.21	230	32	36	34	6	3	1	3	7	4	8	7
A36	776	776	2.22	2.22	0.21	250	34	38	36	6	3	1	3	7	4	8	7
Inorganic PCM																	
SP29 eu	1500	1600	2	2	0.5	200	27	30	28.5	4	7	8	3	1	5	6	2
SP31	1250	1350	2	2	0.5	210	31	33	32	4	7	8	6	1	5	6	2
S32	1460	1460	1.9	1.9	0.51	220	30	34	32	3	8	7	6	1	3	6	3
S34	2100	2100	2.1	2.1	0.52	140	32	36	34	3	8	7	6	1	3	6	3
C28	1500	1500	3	5	0.98	154	27	31	29	3	8	7	6	1	3	6	3
C32	1500	1500	3	6	1.08	145	28	32	30	3	8	7	6	1	3	6	3
Sodium sulphate decahydrate (Na ₂ SO ₄ ·10H ₂ O)	1460	1460	2	2	0.25	228	27.3	35	31.15	3	8	7	6	1	3	6	3
Biobased PCM																	
Puretemp 28	860	950	2.34	2.54	0.25	190	26.1	29.5	28.1	6	3	1	2	8	8	3	6
Puretemp 29	850	940	1.77	1.94	0.25	202	27.3	30.4	29	6	3	1	2	8	8	3	6
Puretemp 37	840	920	2.63	2.21	0.25	210	37	41.5	38.1	6	3	1	2	8	8	3	6
Beef tallow	846	945	2.25	2.25	0.174	86.6	30	33	31.5	6	2	1	1	8	8	3	7
PFAD	860	910	1.72	1.90	0.22	82.52	32.21	34.97	33.59	6	3	1	3	8	8	3	6

Appendix B. Appendix 2

The subjective judgements required by the AHP method were provided through a panel of five experts, selected so that three viewpoints involved in the design of a hybrid BTMS are represented; vehicle integration, thermal-management products and research. The industrial members were a senior battery-pack thermal engineer involved in the design and validation of EV battery systems, and an application engineer specialised in PCM-based thermal-management products. The academic members were three researchers working respectively on battery thermal management, latent heat thermal energy storage, and multi-criteria decision analysis applied to energy systems. All panel members have more than ten years of experience in their field. The authors acted only as facilitators and did not score the criteria themselves.

A simple and reproducible three-step procedure was adopted. (i) Each expert received a short questionnaire describing the design problem and the definitions of the 12 criteria (Section 2.3 and Appendix 1) and independently rated the importance of each criterion on Saaty's 1–9 scale [86]. Rating each criterion once, instead of the pairwise comparisons of a 12×12 matrix, keeps the effort required from each expert reasonable and avoids the contradictory judgements that frequently appear in large comparison matrices. (ii) The five individual ratings were combined using the geometric mean. This choice follows directly from the ratio nature of AHP judgements, so that the aggregated matrix remains reciprocal ($c_{ji} = 1/c_{ij}$) and is identical whether the individual scores or the individual pairwise ratios are aggregated, which is not the case with the arithmetic mean. The aggregated scores were then rounded to the nearest integer of Saaty's scale. (iii) The resulting group vector was returned to the panel in a second, Delphi-type round, together with the justification given below, and was accepted by consensus.

The consensus scores, which constitute the importance vector *Coeff* of Section 4.2, are *Coeff* = [9, 8, 3, 3, 3, 3, 3, 2, 1, 1, 1] for [$T_{\max}$, $\Delta T_{\max}$, ED, δ , θ , γ , ξ , ϕ , ϖ , ζ , o , q]. They define three priority levels, each corresponding to a distinct engineering role of the criteria in the BTMS:

Level 1 ($T_{\max} = 9$, $\Delta T_{\max} = 8$). Keeping the cells below their temperature limit and the pack thermally uniform is the primary function of any BTMS. Exceeding the temperature threshold accelerates degradation and increases the risk of thermal runaway, while cell-to-cell gradients lead to uneven ageing within the pack. A design that fails on these two points cannot be compensated by any material advantage, which justifies their dominant scores. $T_{\max}$ is scored marginally above $\Delta T_{\max}$ because a temperature excursion is safety-critical, whereas a moderate gradient mainly affects the lifetime of the pack.

Level 2 (ED, δ , θ , γ , ξ , $\phi = 3$). The energy density and the mass ratio quantify the penalty of the BTMS on the vehicle range, while thermal stability, supercooling, corrosiveness and cost determine whether a PCM can be reliably and economically integrated and maintained over the service life of the pack. These criteria discriminate between designs that already satisfy Level 1 but cannot override it, which is reflected by a ratio of about 3 between the two levels.

Level 3 ($\varpi = 2$; ζ , o , $q = 1$). In the studied architecture the PCM is sealed inside the battery module, so that the exposure of the occupants to toxic or flammable material is primarily managed at the pack level rather than by the design variables optimised here. Toxicity is kept slightly above the other three criteria because it also concerns the handling of the PCM during manufacturing and maintenance. Environmental impact and recyclability are relevant to the sustainability of the product, but they do not affect the thermal function targeted by the optimisation. These criteria are nevertheless not ignored, they still carry 12.5% of the AHP weights (see Table 3).

The AHP comparison matrix is obtained directly as $c_{ij} = C_i/C_j$ (Section 4.2). Since every element is the ratio of two consensus scores, this matrix is perfectly consistent ($\lambda_{\max} = n = 12$, CI = CR = 0), and its normalised principal eigenvector equals the normalised consensus vector, which yields the AHP weights of Table 3. For readability, Table 2-A reports the same judgements on Saaty's discrete scale, each ratio being rounded to the nearest admissible value.

Table 2-A
Pairwise comparison matrix for the 12 evaluation criteria.

Criteria	$T_{\max}$	$\Delta T_{\max}$	ED	δ	θ	γ	ξ	ϕ	ϖ	ζ	o	q
$T_{\max}$	1	1	3	3	3	3	3	3	5	9	9	9
$\Delta T_{\max}$	1	1	3	3	3	3	3	3	4	8	8	8
ED	1/3	1/3	1	1	1	1	1	1	2	3	3	3
δ	1/3	1/3	1	1	1	1	1	1	2	3	3	3
θ	1/3	1/3	1	1	1	1	1	1	2	3	3	3
γ	1/3	1/3	1	1	1	1	1	1	2	3	3	3
ξ	1/3	1/3	1	1	1	1	1	1	2	3	3	3
ϕ	1/3	1/3	1	1	1	1	1	1	2	3	3	3
ϖ	1/5	1/4	1/2	1/2	1/2	1/2	1/2	1/2	1	2	2	2
ζ	1/9	1/8	1/3	1/3	1/3	1/3	1/3	1/3	1/2	1	1	1
o	1/9	1/8	1/3	1/3	1/3	1/3	1/3	1/3	1/2	1	1	1
q	1/9	1/8	1/3	1/3	1/3	1/3	1/3	1/3	1/2	1	1	1

The consistency of the discrete matrix of Table 2-A is evaluated with Eqs. (41) and (42) of Section 2.3. Its principal eigenvalue is $\lambda_{\max} = 12.021$. Then the Consistency Index (CI) for this matrix is computed:

$$CI = \frac{12.021 - 12}{11} = 0.0019$$

The CR compares the CI with the random index (RI), i.e. the mean CI of randomly generated reciprocal matrices of the same order. For a 12×12 matrix, Saaty's tabulated value is RI = 1.48:

$$CR = \frac{CI}{RI}$$

$$CR = \frac{0.0019}{1.48} = 0.0013$$

CR = 0.0013 is lower than the acceptance threshold of 0.10, rounding the exact ratios to Saaty's discrete scale introduces only a negligible

inconsistency, and the eigenvector weights of Table 2-A differ from the AHP weights of Table 3 by less than 0.012 in absolute value.

Beyond internal consistency, the subjective weights are corroborated by the results of the study itself. The ranking of the 78,000 configurations obtained with the AHP weights is strongly correlated with that obtained with the purely data-driven MEREC method ($SCC = 0.948$) and with SWARA ($SCC = 0.927$) (see Table 6), and the three methods select the same LC configuration (C_1) with very similar thermal performance ($T_{\max} = 31.28\text{--}31.80\text{ }^{\circ}\text{C}$, $\Delta T_{\max} = 0.18\text{--}0.33\text{ }^{\circ}\text{C}$, see Table 4). The expert judgements therefore do not bias the optimisation arbitrarily, they make explicit the priority given to thermal performance, which is the primary function of a BTMS.

Appendix C. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.applthermaleng.2026.133587>.

Data availability

Data will be made available on request.

References

- [1] D. Ragoobur, S.A. Saran, S. Abolfathi, From conflict to climate crisis: how wars shape the future environment, *J. Environ. Manag.* 408 (2026) 129692, <https://doi.org/10.1016/j.jenvman.2026.129692>.
- [2] T. Yokuş, A. Ay, N. Yokuş, Energy price crisis and crash early warning system, *Energ. Strat. Rev.* 64 (2026) 102069, <https://doi.org/10.1016/j.esr.2026.102069>.
- [3] Y. Nishimura, Y. Ji, B. Sun, Geopolitical crises, financial markets, and intraday volatility spillovers, *N. Am. J. Econ. Finance* 82 (2026) 102571, <https://doi.org/10.1016/j.najef.2025.102571>.
- [4] R. Kumar, M.T. Alam, A.K. Gupta, Spoiler integration and geometric optimization for superior air-cooling in diverse configurations of cylindrical lithium-ion battery packs, *Int. J. Therm. Sci.* 220 (2026) 110423, <https://doi.org/10.1016/j.ijsht.2025.110423>.
- [5] P. Li, S. Luo, G. Hao, K. Sun, Q. Liu, M. Möller, et al., Pollutant-free pyrolysis strategy for direct upgrading of cathode materials from spent lithium-ion batteries, *J. Hazard. Mater.* 481 (2025) 136553, <https://doi.org/10.1016/j.jhazmat.2024.136553>.
- [6] S. Landini, T.S. O'Donovan, Experimental investigation of lithium-ion cells ageing under isothermal conditions for optimal lifetime performance, *J. Energy Storage* 48 (2022) 103680, <https://doi.org/10.1016/j.est.2021.103680>.
- [7] S. Landini, J. Leworthy, T.S. O'Donovan, A review of phase change materials for the thermal management and isothermalisation of Lithium-ion cells, *J. Energy Storage* 25 (2019) 100887, <https://doi.org/10.1016/j.est.2019.100887>.
- [8] D. Srivastav, N.D. Patil, P.C. Shukla, Bio-based phase change materials for battery thermal management: A numerical investigation for a single Li-ion cell, *Appl. Therm. Eng.* 278 (2025) 127346, <https://doi.org/10.1016/j.applthermaleng.2025.127346>.
- [9] D. Zhang, Y. Yu, W. Yang, X. Zhang, C. Yu, Q. Zhang, Research on the performance of battery thermal management system based on bionic coupling structure and multi-objective optimization, *J. Energy Storage* (2025) 119034, <https://doi.org/10.1016/j.est.2025.119034>.
- [10] Z. Wu, H. Chen, L. Jiang, P. Zhang, Z. Ji, D. Luo, Thermal management of lithium-ion batteries using a PCM-HP-TEC hybrid BTMS: A numerical study, *Int. Commun. Heat Mass Transfer* 169 (2025) 109702, <https://doi.org/10.1016/j.icheatmasstransfer.2025.109702>.
- [11] A.O. Ali, O. Abdelrehim, M.M. Saafan, M.R. Elmarghany, A.M. Hamed, Comprehensive review of battery management systems for electric vehicles: thermal management, charging strategies, and emerging technologies, *J. Power Sources* 658 (2025) 238269, <https://doi.org/10.1016/j.jpowsour.2025.238269>.
- [12] A. Dhanasekaran, Y. Subramanian, M. Thang Le, R. Dhanasekaran, S.A. Ma, R. K. Gubendiran, et al., Battery thermal management systems for electric vehicles: a review of current status, opportunities, and future challenges, *J. Energy Storage* 166 (2026) 122330, <https://doi.org/10.1016/j.est.2026.122330>.
- [13] M.A. Bamdezh, G.R. Molaeimanesh, The path from conventional battery thermal management systems to hybrid battery thermal management systems for electric vehicles, opportunities and challenges, *J. Energy Storage* 100 (2024) 113160, <https://doi.org/10.1016/j.est.2024.113160>.
- [14] T.A. Takiso, J. Yu, Research progress on the optimization of thermal management systems for lithium-ion batteries in new energy vehicles, *J. Energy Storage* 134 (2025) 118144, <https://doi.org/10.1016/j.est.2025.118144>.
- [15] X. Li, Z. Zhang, X. Zhao, S. Liu, H. Li, Y. Wang, How to select cooling methods for Li-ion batteries? –A review from the perspective of heat flux, *J. Energy Storage* 108 (2025) 115072, <https://doi.org/10.1016/j.est.2024.115072>.
- [16] I. Issah, M.M. Noor, K. Kadirgama, N. Asliffattahi, L. Samyilingam, C.K. Kok, et al., Battery thermal management systems: from conventional approaches to hybrid configurations, *Sustain. Mater. Technol.* 46 (2025) e01711, <https://doi.org/10.1016/j.susmat.2025.e01711>.
- [17] H. Khoharo, J. Selvaraj, M. Hasanuzzaman, L. Kumar, R. Manghwar, Global advancement, prospect and challenges of battery thermal management systems: A comprehensive review, *Renew. Sust. Energ. Rev.* 222 (2025) 115923, <https://doi.org/10.1016/j.rser.2025.115923>.
- [18] X. Li, W. Yang, L. Yin, S. Zhang, Y. Wu, Y. Mao, et al., Advancing lithium battery safety: introducing a composite phase change material with anti-leakage and fire-resistant properties, *ETransportation* 23 (2025) 100387, <https://doi.org/10.1016/j.etrans.2024.100387>.
- [19] Y. Su, J. Shen, X. Chen, X. Xu, S. Shi, X. Wang, et al., Bio-based eutectic composite phase change materials with enhanced thermal conductivity and excellent shape stabilization for battery thermal management, *J. Energy Storage* 100 (2024) 113712, <https://doi.org/10.1016/j.est.2024.113712>.
- [20] A.C. Nunna, O. Galteland, L. Georges, Y. Zong, Optimal control of a bio-based phase change material thermal energy storage for demand response, *Energy Convers. Manag.* 326 (2025) 119476, <https://doi.org/10.1016/j.enconman.2024.119476>.
- [21] A. Dwivedi, R. Kumar, V. Goel, S. Rana, R. Kumar, A. Kumar, A comprehensive review on heat pipe-assisted hybrid battery thermal management strategies: opportunities, challenges and its future aspects, *J. Energy Storage* 112 (2025) 115475, <https://doi.org/10.1016/j.est.2025.115475>.
- [22] A. Awasthi, N. Nirmalkar, A.K. Tiwari, A review of PCM based hybrid battery thermal management systems for the prismatic lithium-ion batteries of the electric vehicle, *Future Batter.* 5 (2025) 100035, <https://doi.org/10.1016/j.fub.2025.100035>.
- [23] S. Xin, C. Wang, H. Xi, Thermal management scheme and optimization of cylindrical lithium-ion battery pack based on air cooling and liquid cooling, *Appl. Therm. Eng.* 224 (2023) 120100, <https://doi.org/10.1016/j.applthermaleng.2023.120100>.
- [24] D.S. Jang, S. Yun, S.H. Hong, W. Cho, Y. Kim, Performance characteristics of a novel heat pipe-assisted liquid cooling system for the thermal management of lithium-ion batteries, *Energy Convers. Manag.* 251 (2022) 115001, <https://doi.org/10.1016/j.enconman.2021.115001>.
- [25] R. Feng, P. Huang, Z. Tang, Y. He, Z. Bai, Experimental and numerical study on the cooling performance of heat pipe assisted composite phase change material-based battery thermal management system, *Energy Convers. Manag.* 272 (2022) 116359, <https://doi.org/10.1016/j.enconman.2022.116359>.
- [26] A. Afass, B. Lamrani, B. Lebrouhi, M.A. Tankari, M. Karkri, S. Landini, et al., Thermal assessment of Li-ion batteries incorporating phase change materials using a new 2D model, *Energy Convers. Manag.*: X 27 (2025) 101051, <https://doi.org/10.1016/j.ecmx.2025.101051>.
- [27] S. Hekmat, G.R. Molaeimanesh, Hybrid thermal management of a Li-ion battery module with phase change material and cooling water pipes: an experimental investigation, *Appl. Therm. Eng.* 166 (2020) 114759, <https://doi.org/10.1016/j.applthermaleng.2019.114759>.
- [28] H. Najafi Khaboshan, K. Kadirgama, D. Ramasamy, V. Talele, P. Zhao, H. Tyagi, et al., Thermal uniformity analysis of a hybrid battery pack using integrated phase change material, metal foam, and counterflow minichannels, *Appl. Therm. Eng.* 259 (2025) 124910, <https://doi.org/10.1016/j.applthermaleng.2024.124910>.
- [29] Y. Wu, L. Lv, F. Wu, L. Wei, H. Li, H. Zhou, Numerical simulation of phase change material-assisted liquid cooling with gear-shaped fins for battery thermal management, *Appl. Therm. Eng.* 284 (2026) 128983, <https://doi.org/10.1016/j.applthermaleng.2025.128983>.
- [30] Z. Liu, B. Qiao, N. Qi, Research on the fuzzy proportional-integral-derivative control strategy of a hybrid battery thermal management system under different ambient temperatures, *J. Energy Storage* 153 (2026) 121039, <https://doi.org/10.1016/j.est.2026.121039>.
- [31] Z. Liu, C. Xiong, X. Du, Research on the optimization control strategy of a battery thermal management system based on serpentine liquid cooling combined with phase change material, *J. Power Sources* 630 (2025) 236127, <https://doi.org/10.1016/j.jpowsour.2024.236127>.
- [32] B. Zhang, Z. Zeng, N. Yuan, H. Shi, Numerical investigation of lithium-ion battery thermal management system performance influenced by physical properties of PCM, *J. Energy Storage* 117 (2025) 116141, <https://doi.org/10.1016/j.est.2025.116141>.
- [33] E.B. Agyekum, F. Odoi-Yorke, S. Mirzalizadeh, M. Abdullah, F.L. Rashid, A. K. Hussein, Review of trends and emerging optimization techniques for battery thermal management – traditional and bibliometric approach, *J. Energy Storage* 119 (2025) 116437, <https://doi.org/10.1016/j.est.2025.116437>.
- [34] D. Zheng, X. Chen, X. Han, N. Chu, Performance study and optimization of a hybrid liquid cooling integrated with vapor chamber and phase change material for cylindrical lithium-ion battery, *Appl. Therm. Eng.* 290 (2026) 130103, <https://doi.org/10.1016/j.applthermaleng.2026.130103>.
- [35] Z. Bai, Y. Jiang, K. Zhong, Q. Luo, Z. Liang, C. Wang, Multi-objective optimization of heat transfer performance of immersion-cooling battery thermal management

- system based on the shunt structure, *J. Energy Storage* 127 (2025) 117102, <https://doi.org/10.1016/j.est.2025.117102>.
- [36] Z. Liu, X. Zhang, N. Qi, Performance analysis and multi-objective optimization of a hybrid thermal management system for lithium-ion batteries based on PCM and liquid cooling, *J. Energy Storage* 135 (2025) 118264, <https://doi.org/10.1016/j.est.2025.118264>.
- [37] H. Yang, N. Liu, M. Li, M. Gu, Q. Gao, Design and optimization of heat pipe-assisted liquid cooling structure for power battery thermal management based on NSGA-II and entropy weight-TOPSIS method, *Appl. Therm. Eng.* 272 (2025) 126416, <https://doi.org/10.1016/j.applthermaleng.2025.126416>.
- [38] C. Wu, X. Yuan, B. Kong, Y. Zou, H. Shi, Innovative liquid cooling channel enhanced battery thermal management (BTM) structure based on stepwise optimization method, *J. Energy Storage* 81 (2024) 110485, <https://doi.org/10.1016/j.est.2024.110485>.
- [39] A. Sharma, S. Sreedhara, M. Khatamifar, W. Lin, Comparative investigation of different liquid-cooled battery thermal management systems (LC-BTMS) designs for battery module of electric vehicle, *Appl. Therm. Eng.* 292 (2026) 130436, <https://doi.org/10.1016/j.applthermaleng.2026.130436>.
- [40] X. Chen, J. Shen, X. Xu, X. Wang, Y. Su, J. Qian, et al., Performance of thermal management system for cylindrical battery containing bionic spiral fin wrapped with phase change material and embedded in liquid cooling plate, *Renew. Energy* 223 (2024) 120087, <https://doi.org/10.1016/j.renene.2024.120087>.
- [41] F. Zhang, X. Lu, L. Zhang, K. Xiao, F. Lu, Y. He, et al., Bionic liquid cooling plate thermal management system based on flow resistance-thermal resistance model, *Int. J. Therm. Sci.* 190 (2023) 108336, <https://doi.org/10.1016/j.ijthermalsci.2023.108336>.
- [42] G. Hu, A. Wang, Z. Yang, P. Tan, An efficient physics-based thermal management model for cylindrical battery packs: from a system analysis perspective, *J. Energy Storage* 111 (2025) 115397, <https://doi.org/10.1016/j.est.2025.115397>.
- [43] Z. Wang, R. Bao, N. Zhang, S. Hong, Q. Gao, H. Yang, Performance study and optimization of battery thermal management system for integrated cooling/heating of cylindrical lithium-ion battery modules, *J. Energy Storage* 147 (2026) 120109, <https://doi.org/10.1016/j.est.2025.120109>.
- [44] M. Mesgarpour, M. Mir, R. Alizadeh, J.M.N. Abad, E.P. Borj, An evaluation of the thermal behaviour of a lithium-ion battery pack with a combination of pattern-based artificial neural networks (PBANN) and numerical simulation, *J. Energy Storage* 47 (2022) 103920, <https://doi.org/10.1016/j.est.2021.103920>.
- [45] Y. Wu, A.C.Y. Yuen, C. Mo, X. Huang, Modelling and optimization of a thermal management and barrier integration structure by coupling CFD and reduced-order thermal resistance network, *Energy Convers. Manag.* 343 (2025) 120188, <https://doi.org/10.1016/j.enconman.2025.120188>.
- [46] Y.S. Jeong, K.N. Chandran, M.Y. Ha, J.K. Min, Coupled lumped parameter and enthalpy-based model for hybrid passive battery thermal management using thermal projection mapping, *Appl. Therm. Eng.* 295 (2026) 130760, <https://doi.org/10.1016/j.applthermaleng.2026.130760>.
- [47] S. Lee, J.K. Min, J.S. Yang, Development of a one-dimensional equivalent thermal network-based prediction model for natural convection heat transfer characteristics in stacked cells, *Int. Commun. Heat Mass Transfer* 178 (2026) 111880, <https://doi.org/10.1016/j.icheatmasstransfer.2026.111880>.
- [48] A.J. Torregrosa, A. Broatch, P. Olmeda, L. Agizza, Analysis of the improvement of a lithium-ion battery module cooling system employing nanofluid and nano encapsulated phase change materials by means of a lumped electro-thermal model, *J. Energy Storage* 70 (2023), <https://doi.org/10.1016/j.est.2023.107995>.
- [49] J. He, M. Sazzad Hosen, R. Youssef, T. Kalogiannis, J. Van Mierlo, M. Berecibar, A lumped electro-thermal model for a battery module with a novel hybrid cooling system, *Appl. Therm. Eng.* 221 (2023) 119874, <https://doi.org/10.1016/j.applthermaleng.2022.119874>.
- [50] A. Broatch, P. Olmeda, X. Margot, L. Agizza, A generalized methodology for lithium-ion cells characterization and lumped electro-thermal modelling, *Appl. Therm. Eng.* 217 (2022) 119174, <https://doi.org/10.1016/j.applthermaleng.2022.119174>.
- [51] J. Lu, D. Zhuang, G. Ding, G. Li, Y. Wang, A distributed parameter model of refrigerant-cooled multi-channel evaporator for battery thermal management, *Energy* 304 (2024) 132170, <https://doi.org/10.1016/j.energy.2024.132170>.
- [52] Z. Yang, X. Wu, S. Wang, Z. Rao, K. Chen, An efficient thermal resistance network model for battery thermal management system with phase change materials and cold plates, *Int. Commun. Heat Mass Transfer* 178 (2026) 111613, <https://doi.org/10.1016/j.icheatmasstransfer.2026.111613>.
- [53] W. Zhu, F. Lei, H. Zhong, X. Jiang, Thermal performance revival of composite PCM for hybrid BTMSs by architecture and formula integrated optimization, *Appl. Therm. Eng.* 210 (2022) 118320, <https://doi.org/10.1016/j.applthermaleng.2022.118320>.
- [54] D. Kong, R. Peng, P. Ping, J. Du, G. Chen, J. Wen, A novel battery thermal management system coupling with PCM and optimized controllable liquid cooling for different ambient temperatures, *Energy Convers. Manag.* 204 (2020) 112280, <https://doi.org/10.1016/j.enconman.2019.112280>.
- [55] Y. Zheng, Y. Shi, Y. Huang, Optimisation with adiabatic interlayers for liquid-dominated cooling system on fast charging battery packs, *Appl. Therm. Eng.* 147 (2019) 636–646, <https://doi.org/10.1016/j.applthermaleng.2018.10.090>.
- [56] S. Cailliez, D. Chalet, P. Mannesiez, Simultaneous identification of the heat capacity and the anisotropic thermal conductivities of a Li-ion pouch cell by a non-destructive analytical approach, *J. Power Sources* 542 (2022) 231751, <https://doi.org/10.1016/j.jpowsour.2022.231751>.
- [57] A. Nazari, S. Farhad, Heat generation in lithium-ion batteries with different nominal capacities and chemistries, *Appl. Therm. Eng.* 125 (2017) 1501–1517, <https://doi.org/10.1016/j.applthermaleng.2017.07.126>.
- [58] D. Chalise, W. Lu, V. Srinivasan, R. Prasher, Heat of mixing during fast charge/discharge of a Li-ion cell: a study on NMC523 cathode, *J. Electrochem. Soc.* 167 (2020) 090560, <https://doi.org/10.1149/1945-7111/abaf71>.
- [59] R. Mehta, A. Gupta, Significance of heat of mixing analysed using a pseudo two-dimensional thermo-electrochemical model of lithium-ion cells, *Electrochim. Acta* 475 (2024) 143509, <https://doi.org/10.1016/j.electacta.2023.143509>.
- [60] Z. Chen, Y. Qin, Z. Dong, J. Zheng, Y. Liu, Numerical study on the heat generation and thermal control of lithium-ion battery, *Appl. Therm. Eng.* 221 (2023) 119852, <https://doi.org/10.1016/j.applthermaleng.2022.119852>.
- [61] L.H.J. Rajmakers, D.L. Danilov, R.-A. Eichel, P.H.L. Notten, A review on various temperature-indication methods for Li-ion batteries, *Appl. Energy* 240 (2019) 918–945, <https://doi.org/10.1016/j.apenergy.2019.02.078>.
- [62] X. Wu, Y. Lu, H. Ouyang, X. Ren, J. Yang, H. Guo, et al., Theoretical and experimental investigations on liquid immersion cooling battery packs for electric vehicles based on analysis of battery heat generation characteristics, *Energy Convers. Manag.* 310 (2024) 118478, <https://doi.org/10.1016/j.enconman.2024.118478>.
- [63] R. Waser, S. Maranda, A. Stamatiou, M. Zaglio, J. Worlitschek, Modeling of solidification including supercooling effects in a fin-tube heat exchanger based latent heat storage, *Sol. Energy* 200 (2020) 10–21, <https://doi.org/10.1016/j.solener.2018.12.020>.
- [64] B. Lamrani, B.E. Lebrouhi, Y. Khattari, T. Kousksou, A simplified thermal model for a lithium-ion battery pack with phase change material thermal management system, *J. Energy Storage* 44 (2021) 103377, <https://doi.org/10.1016/j.est.2021.103377>.
- [65] B.E. Lebrouhi, B. Lamrani, M. Ouassaid, M. Abd-Lefdil, M. Maaroufi, T. Kousksou, Low-cost numerical lumped modelling of lithium-ion battery pack with phase change material and liquid cooling thermal management system, *J. Energy Storage* 54 (2022) 105293, <https://doi.org/10.1016/j.est.2022.105293>.
- [66] A. Afass, S. Landini, O. Elghaz, B. Lamrani, T. Kousksou, Analytical solution and parametric design of bio-PCM-based passive BTMS for cylindrical lithium-ion cells under lumped model assumptions, *Int. J. Therm. Sci.* 221 (2026) 110466, <https://doi.org/10.1016/j.ijthermalsci.2025.110466>.
- [67] H.E. Bell, Gershgorin's theorem and the zeros of polynomials, *Am. Math. Mon.* 72 (1965) 292–295, <https://doi.org/10.2307/2313703>.
- [68] S. Shan, L. Li, Q. Xu, L. Ling, Y. Xie, H. Wang, et al., Numerical investigation of a compact and lightweight thermal management system with axially mounted cooling tubes for cylindrical lithium-ion battery module, *Energy* 274 (2023) 127410, <https://doi.org/10.1016/j.energy.2023.127410>.
- [69] M.B. Awan, Z. Ma, W. Lin, A.K. Pandey, V.V. Tyagi, A characteristic-oriented strategy for ranking and near-optimal selection of phase change materials for thermal energy storage in building applications, *J. Energy Storage* 57 (2023) 106301, <https://doi.org/10.1016/j.est.2022.106301>.
- [70] P. GaneshKumar, A. Ajithkumar, V. Sivalingam, S. Divya, T.H. Oh, S. Pandiaraj, et al., Exploring the cost-effective and environmentally friendly energy storage materials for solar desalination: A multi-criteria decision-making framework, *J. Energy Storage* 132 (2025) 117720, <https://doi.org/10.1016/j.est.2025.117720>.
- [71] A. Thakur, V. Kumar, V. Goel, Multi-criteria optimization and assessment of phase-change materials for indirect concentrated solar cookers, *J. Energy Storage* 153 (2026) 120929, <https://doi.org/10.1016/j.est.2026.120929>.
- [72] A. Ajithkumar, P. GaneshKumar, A greener approach for selecting organic PCM in solar thermal collectors using the MCDM framework, *Sol. Energy* 305 (2026) 114283, <https://doi.org/10.1016/j.solener.2025.114283>.
- [73] Q. Al-Yasiri, M. Szabo, Selection of phase change material suitable for building heating applications based on qualitative decision matrix, *Energy Convers. Manage.* 12 (2021) 100150, <https://doi.org/10.1016/j.enconman.2021.100150>.
- [74] H. Dong, X. Chen, S. Yan, D. Wang, J. Han, Z. Guan, et al., Multi-objective optimization of lithium-ion battery pack thermal management systems with novel bionic lotus leaf channels using NSGA-II and RSM, *Energy* 314 (2025) 134226, <https://doi.org/10.1016/j.energy.2024.134226>.
- [75] Md Sahabuddin, I. Khan, Multi-criteria decision analysis methods for energy sector's sustainability assessment: robustness analysis through criteria weight change, *Sustain. Energy Techn. and Assess.* 47 (2021) 101380, <https://doi.org/10.1016/j.seta.2021.101380>.
- [76] Q. Hu, M. Wu, C. Wang, Y. Da, H. Du, Design and multi-objective optimization of efficient UAV battery thermal management system using PCM–air synergistic cooling strategy, *Appl. Therm. Eng.* 297 (2026) 130845, <https://doi.org/10.1016/j.applthermaleng.2026.130845>.
- [77] C.-H. Hsieh, D. Bakry, T. Daim, Technology assessment through a hybrid scenario-based decision making: case of wind energy, *Technol. Soc.* 85 (2026) 103205, <https://doi.org/10.1016/j.techsoc.2025.103205>.
- [78] C.E. Shannon, A mathematical theory of communication, *Bell Syst. Tech. J.* 27 (1948) 379–423, <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>.
- [79] P.P. Dwivedi, D.K. Sharma, Evaluation and ranking of battery electric vehicles by Shannon's entropy and TOPSIS methods, *Math. Comput. Simul.* 212 (2023) 457–474, <https://doi.org/10.1016/j.matcom.2023.05.013>.
- [80] A. M., D. Das, Multi-criteria evaluation of green microalgal variants for biodiesel using an integrated CRITIC–BWM–CoCoSo screening framework, *Biomass Bioenergy* 210 (2026) 109063, <https://doi.org/10.1016/j.biombioe.2026.109063>.
- [81] A. Azhar, O. Imghoure, Z. Younsi, N. Belouaggadia, N. Sebaibi, Selection of high-performance phase change materials for enhanced building thermal management using hybrid multi-criteria decision-making, *Appl. Therm. Eng.* 292 (2026) 130393, <https://doi.org/10.1016/j.applthermaleng.2026.130393>.

- [82] N. Kumar, J. Mahanta, A matrix norm-based Pythagorean fuzzy metric and its application in MEREC-SWARA-VIKOR framework for solar panel selection, *Appl. Soft Comput.* 158 (2024) 111592, <https://doi.org/10.1016/j.asoc.2024.111592>.
- [83] M.R. Seikh, P. Chatterjee, Sustainable strategies for electric vehicle adoption: a confidence level-based interval-valued spherical fuzzy MEREC-VIKOR approach, *Inf Sci (N Y)* 699 (2025) 121814, <https://doi.org/10.1016/j.ins.2024.121814>.
- [84] A.A. Amiri, M.N. Wahid, A.S. Al-Buraiki, A. Al-Sharafi, A strategic multi-criteria decision-making framework for renewable energy source selection in Saudi Arabia using AHP-TOPSIS, *Renew. Energy* 236 (2024) 121523, <https://doi.org/10.1016/j.renene.2024.121523>.
- [85] A. Ishizaka, A. Labib, Review of the main developments in the analytic hierarchy process, *Expert Syst. Appl.* 38 (2011) 14336–14345, <https://doi.org/10.1016/j.eswa.2011.04.143>.
- [86] B.C. Pinheiro, P.H. de Mello Sant'Ana, AHP-based decision making to selecting energy-efficient air conditioning equipments in a commercial building, *Energy Buildings* 329 (2025) 115281, <https://doi.org/10.1016/j.enbuild.2025.115281>.
- [87] S.V. Tyagi, M.K. Singhal, M.L. Kansal, Energy, economic, and environmental (3E) analysis for optimal off-grid hybrid energy system considering various battery technologies: a multi-criteria decision-based approach, *Energy Convers. Manag.* 344 (2025) 120271, <https://doi.org/10.1016/j.enconman.2025.120271>.
- [88] S.J. Hosseini Dehshiri, M. Amiri, Evaluating challenges of implementing industry 5.0 in the renewable energy supply chain toward sustainability: A comparative analysis using decision-making approaches, *Energy Strat. Rev.* 59 (2025) 101761, <https://doi.org/10.1016/j.esr.2025.101761>.
- [89] B.S. Chamarthi, P. Sandilya, A multi criteria decision analysis to select phase change material for packed bed cryogenic energy recovery systems, *J. Energy Storage* 143 (2026) 119780, <https://doi.org/10.1016/j.est.2025.119780>.
- [90] A. Ajithkumar, P. GaneshKumar, A systematic framework for the optimum selection of organic PCM in sustainable solar drying process: A multi-criteria decision-making methodology, *J. Energy Storage* 116 (2025) 116080, <https://doi.org/10.1016/j.est.2025.116080>.
- [91] X. Chen, W. Yang, J. Shen, X. Xu, F. Zhou, Thermal performance of hybrid battery thermal management system with air cooling and phase change material embedding biomimetic variable section fins, *Appl. Therm. Eng.* 231 (2023) 120985, <https://doi.org/10.1016/j.applthermaleng.2023.120985>.
- [92] Y. Li, Z. Chen, Y. Feng, M. Liu, C. Kang, K. Yang, et al., A novel petal-type battery thermal management system with dual phase change materials, *Int. J. Heat Mass Transf.* 207 (2023) 123989, <https://doi.org/10.1016/j.jheatmasstransfer.2023.123989>.
- [93] Rubitherm Technologies GmbH, <https://www.rubitherm.eu/en/productcategory/anorganische-pcm-sp>, 2026.
- [94] PCM products, https://www.pcmproducts.net/Phase_Change_Material_Products.htm, 2026.
- [95] Rubitherm Technologies GmbH, <https://www.rubitherm.eu/en/productcategory/organische-pcm-rt>, 2026.
- [96] G. Poongavanam, V. Sivalingam, R. Prabakaran, M. Salman, S.C. Kim, Selection of the best refrigerant for replacing R134a in automobile air conditioning system using different MCDM methods: A comparative study, *Case Stud. Therm. Eng.* 27 (2021) 101344, <https://doi.org/10.1016/j.csite.2021.101344>.
- [97] F. Ecer, A consolidated MCDM framework for performance assessment of battery electric vehicles based on ranking strategies, *Renew. Sust. Energy Rev.* 143 (2021) 110916, <https://doi.org/10.1016/j.rser.2021.110916>.
- [98] D. Zhou, G.S.F. Shire, Y. Tian, Parametric analysis of influencing factors in phase change material wallboard (PCMw), *Appl. Energy* 119 (2014) 33–42, <https://doi.org/10.1016/j.apenergy.2013.12.059>.
- [99] M. Serikawa, M. Satoh, M. Mae, Y. Nozue, Y. Hayashi, Numerical models of heat storage with respect to phase change materials considering hysteresis, *J. Energy Storage* 55 (2022) 105758, <https://doi.org/10.1016/j.est.2022.105758>.
- [100] D. Sharma, A. Loukodimou, B. Champel, S. Paul, A review of phase change materials: selection, degradation, and materials compatibility, *J. Energy Storage* 166 (2026) 122473, <https://doi.org/10.1016/j.est.2026.122473>.
- [101] W. Hua, X. Lv, X. Zhang, Z. Ji, J. Zhu, Research progress of seasonal thermal energy storage technology based on supercooled phase change materials, *J. Energy Storage* 67 (2023) 107378, <https://doi.org/10.1016/j.est.2023.107378>.
- [102] W. Hua, X. Xu, X. Zhang, H. Yan, J. Zhang, Progress in corrosion and anti-corrosion measures of phase change materials in thermal storage and management systems, *J. Energy Storage* 56 (2022) 105883, <https://doi.org/10.1016/j.est.2022.105883>.
- [103] A.M. Onaizi, W. Tang, G.F. Huseien, M. Alhassan, S.A. Onaizi, A systematic review on the application progress of phase change materials in energy piles, *Appl. Therm. Eng.* 274 (2025) 126630, <https://doi.org/10.1016/j.applthermaleng.2025.126630>.
- [104] R. Aridi, A. Yehya, Review on the sustainability of phase-change materials used in buildings, *Energy Convers. Manage.* 15 (2022) 100237, <https://doi.org/10.1016/j.ecmx.2022.100237>.
- [105] M. Calati, K. Hooman, S. Mancin, Thermal storage based on phase change materials (PCMs) for refrigerated transport and distribution applications along the cold chain: A review, *Int. J. Thermofluids* 16 (2022) 100224, <https://doi.org/10.1016/j.ijft.2022.100224>.