

Review

Artificial Intelligence in Thermal Energy Storage Systems for Buildings to City-Scale Energy Flexibility: A Review

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Abstract

Buildings account for roughly 37% of energy-related CO₂ emissions, and space cooling already consumes nearly 10% of global electricity. Cooling demand is rising fastest in tropical cities, where air-conditioning could reach 45% of peak load, especially in India by 2050. This review critically examines thermal energy storage (TES) as a flexibility resource across three distinct scales: individual buildings, district heating and cooling networks, and city-level multi-energy systems. Using a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based search of Scopus, Web of Science, and IEEE Xplore with primary and supplementary strings, 4447 records were identified, of which 174 were included. Each quantitative study was classified by validation level (simulation, laboratory, pilot, or operational) and by the centrality of thermal storage. Sensible, latent, and thermochemical storage technologies are compared using energy density (10–500 kWh/m³), efficiency (40–95%), cycle stability, and technology readiness. The review then evaluates the role of artificial intelligence (AI), machine learning, and Internet of Things platforms in forecasting, predictive control, and operational optimization of TES networks. Thirteen method families, grouped into AI and machine learning methods, optimization methods, control methods, and digital enabling technologies, are assessed against six explicitly defined criteria with evidence-coded scores. Among 47 quantitative studies, 37 (78.7%) are simulation-only, and only four (8.5%) report operational data. Direct TES-AI studies report simulated energy savings of 8–64% and peak load reductions of about 35%, whereas field-validated intelligent control reports 17% energy savings in a single real building experiment. The review also identifies inherent drawbacks of artificial intelligence-based operations, including limited interpretability, high data and computational demands, concept drift, and cyber vulnerabilities that increased peak electric load by 17.4% in a simulated attack. A structural imbalance in the literature is evident: most validated deployments remain at the building-scale, whereas urban-scale evidence is confined to district cooling, aquifer and pit storage, and multi-energy hub studies; no study reports the coordinated operation of distributed TES assets across multiple districts. A conceptual framework and a staged roadmap linking building, district, and urban scales are proposed. Priority research needs include urban-scale pilots in tropical climates, techno-economic assessment, interpretable and drift-robust AI, and interoperability standards that support United Nations' Sustainable Development Goals 7, 11, and 13.



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1. Introduction

1.1. Background and Motivation

Urban areas concentrate buildings, industry, and transport, and therefore dominate global energy use and emissions. Cities consequently play a pivotal role in climate mitigation and the transition toward sustainable energy systems [1,2]. The concept of net-zero energy cities, where annual energy demand is balanced by renewable generation, has emerged as a critical pathway for long-term environmental sustainability and energy security. Real net-zero urban energy systems (UESs) require the coordinated integration of renewable energy technologies, advanced energy storage, and intelligent energy management frameworks that balance supply and demand while reducing fossil fuel dependence [3,4]. Within this transformation, net-zero energy buildings (NZEBS) represent the foundational units of sustainable cities. These buildings minimize demand through passive design, efficient envelopes, and optimized heating, ventilation, and air-conditioning (HVAC) systems, supported by renewable energy generation and storage [5].

Rapidly urbanizing countries such as India face additional challenges from rising energy demand and climate variability. The most critical challenge is the rapid growth in cooling demand, driven by population growth, expanding urban infrastructure, higher ambient temperatures, and urban heat island effects [6,7]. Space cooling already accounts for close to 10% of global electricity use, and the worldwide air-conditioner stock is projected to grow from 1.6 to 5.6 billion units by 2050 [8]. In India, air-conditioning could rise from about 10% to 45% of peak electric load by 2050 without efficiency and flexibility measures [8]. The national cooling demand is projected to grow nearly eight-fold between 2017 and 2038 [9]. Cooling demand in buildings accounts for a significant share of electricity consumption in Indian cities [10,11]. This growth stresses electricity infrastructure through peak load, higher operating costs, and increased emissions [12,13]. Addressing these challenges requires solutions that manage thermal loads efficiently while enabling greater integration of renewable energy sources (RES). Thermal energy storage (TES) has gained considerable attention for this role [14,15]. TES systems store excess thermal energy during low-demand periods and release it during peak periods, reducing electricity consumption, improving load management, and enhancing grid stability [16–18]. Sensible heat storage raises the temperature of media such as water, rocks, or molten salts, with the capacity determined by the heat capacity and the temperature difference [19]. Latent heat storage uses phase change materials (PCMs) that absorb and release large amounts of heat during phase transitions, providing higher storage density and near-constant operating temperatures, which are well-suited to building heating and cooling [20,21]. Thermochemical storage uses reversible reactions to reach high energy density and long-duration storage, at the cost of greater system complexity [22].

1.2. Urban Energy Systems: Definition and Scale Boundaries

The term “urban energy system” is used inconsistently in the literature, complicating comparisons across studies. Following Keirstead et al. [23], a UES is defined here as the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area. A UES is therefore not a single technology but a system of systems. It spans buildings, distribution networks, generation and storage assets, and the institutions

that govern them. Building-scale systems (roughly 1 kWh_{th} to 1 MWh_{th} of storage capacity) serve a single building and are controlled by a single owner via a building management system. Building clusters (1–100 MWh_{th}) share centralized plants or thermal loops among several buildings. District-scale systems (100 MWh_{th} to 10 GWh_{th}) distribute heating or cooling through networks serving hundreds of buildings, often with large water tanks, borehole fields, or aquifer storage. Urban or city-scale systems (10 GWh_{th} to 1 TWh_{th}) coordinate multiple districts, couple thermal networks with power, gas, water, and transport infrastructure, and involve municipal planning and regulation. Regional systems (above 1 TWh_{th}) link cities through inter-regional networks and seasonal storage. Capacity alone does not define scale. Three additional criteria are applied consistently in this review: the number of independently owned TES assets under coordinated control (one, several, tens to hundreds, or multiple districts), the administrative boundary of the decision-maker (owner, aggregator, utility, or municipality), and whether the study reports model results or coordinated operation of physical assets. A study is classified as city-scale only if it coordinates TES assets across at least two districts under a common objective. Urban-scale energy system optimization models that treat storage as an aggregated variable are labeled urban (model) and are distinguished from deployed networks. The distinction matters for three reasons. First, the applicable TES technologies differ: PCM modules and water tanks dominate at the building-scale, whereas aquifer, borehole, and pit storage become economical only at the district-scale and above [24,25]. Second, control objectives shift from indoor comfort and utility bills at the building-scale to network hydraulics, peak shaving, and market participation at the district and city scales [26]. Third, the decision-makers change from individual owners to utilities, municipalities, and regulators, so deployment barriers become institutional rather than purely technical. Distribution-grid constraints illustrate this institutional dimension. In Romania, residential prosumer capacity grew from 1.52 MW in 2019 to 5312 MW by April 2026, while the grid saturation index fell from 0.96 to −0.59, and the estimated carrying capacity reached roughly 398,000 prosumers [27]. Flexibility resources such as TES, rather than additional generation, therefore set the pace at which urban systems can absorb renewables. In this review, the phrase intelligent TES network denotes digitally coordinated TES assets operating at least at the district scale. Building-level studies are reviewed as the enabling foundation of such networks and are labeled accordingly.

1.3. Related Reviews and Recent Advances

In recent years, integrating TES with digital and intelligent energy management has attracted increasing attention. AI, smart grid technologies, and Internet of Things (IoT) platforms open new opportunities to optimize TES operation and system-level performance [28–30]. AI-driven algorithms forecast energy demand and renewable energy availability while optimizing TES charging and discharging in real-time [31,32]. IoT-based monitoring platforms complement these capabilities by continuously acquiring data from distributed energy assets [33,34]. Recent literature also highlights the potential of combining advanced materials and AI to improve TES performance. Mohammed et al. [35] reported that incorporating nanomaterials such as Al₂O₃ and CuO into PCMs and nanofluids increased thermal conductivity by up to 28.8%. They also showed that artificial neural networks (ANNs) and particle swarm optimization reached predictive accuracies above 97%, with energy savings of up to 28% in AI-driven PCM-based HVAC systems. Shukla et al. [36] reviewed AI applications in battery energy storage, covering real-time monitoring, state estimation, and predictive maintenance. AI and machine learning (ML) improve the optimization, forecasting, and maintenance of storage assets, resulting in measurable efficiency gains and cost reductions [37]. Hybrid energy systems integrate multiple sources to

improve efficiency and renewable integration in distributed generation, and AI techniques improve their control and reliability despite added system complexity [38]. Li et al. [39] developed an AI-based optimization platform for solid-gas sorption storage, in which ANNs predicted performance with absolute relative errors below 1% and a multi-population genetic algorithm identified optimal adsorbate pressures of 5.2–8.7 bar.

Intelligent control for building energy management has been explored extensively. Lv et al. [40] used digital twins to optimize the scheduling of PCM-integrated walls, thereby preventing battery overcharging in microgrids and reducing economic and environmental costs. Shaterabadi et al. [41] reported 34.6% lower total costs and 51.2% lower pollution for a plus-zero energy building when cost optimization was prioritized. Reinforcement learning (RL) shows strong potential for energy system optimization, with documented efficiency gains but persistent challenges in scalability, interpretability, and integration [42]. Deep learning delivers similar gains for smart-city energy optimization, but at a high computational cost [43]. Liu et al. [44] combined RL with adaptive model predictive control (MPC) for building energy systems, cutting energy consumption by 12.1% while improving photovoltaic (PV) utilization. At infrastructure scale, a bibliometric analysis of large-scale underground energy storage identified intelligent system integration, hybrid storage, and underground biomethanation as emerging themes [45].

Table 1 compares the present study with recent reviews and confirms that most prior work is building- or district-focused. This review makes four specific contributions. First, it defines explicit scale boundaries for TES deployment, from buildings to regions, and maps technologies, capacities, and applications to each scale. Second, it provides a criteria-based comparison of thirteen AI and intelligent digital method families, grouped into AI/ML, optimization, control, and digital enabling technologies, for TES operation using six defined assessment dimensions and an evidence-anchored scoring scale with reported inter-rater agreement and sensitivity analysis. Third, it synthesizes quantified performance evidence across 47 recent building, district, and urban case studies, including reported energy savings, peak reductions, and payback periods, stratified by validation level and by the centrality of TES in the system boundary. Fourth, it identifies deployment barriers and a staged roadmap for tropical cities, with explicit attention to the drawbacks and risks of AI-based operation rather than its benefits alone.

Table 1. Comparison of recent reviews with the present review.

Reference	Main Focus	Scale	Key Technologies	Major Findings	Research Gap
Dora et al. [46]	PCM applications in buildings	Building-level	PCMs, building envelopes	Highlighted improved thermal comfort and annual energy savings through PCM	Limited discussion on urban-scale integration
Hawraa et al. [47]	Nearly zero energy buildings in hot climates	Commercial and residential buildings	PCMs, HVAC, hybrid storage, AI-based EMS	30–50% energy savings using hybrid systems and climate-responsive materials	Primarily focused on NZEB design strategies
Selvam et al. [48]	Hybrid solar-PCM systems for buildings	Building-level	PV, photovoltaic-thermal (PVT), PCM, HVAC integration	Reported efficiencies approaching 80%, HVAC energy reduction up to 40%, and CO ₂ reduction of 120–180 kg annually	Limited focus on urban-scale deployment and digital integration

Table 1. Cont.

Reference	Main Focus	Scale	Key Technologies	Major Findings	Research Gap
Teamah and Teamah [49]	PCM integration in building envelopes	Building envelope scale	PCM walls, roofs, and floors	Reduced building loads by up to 30% and indoor temperature fluctuations to nearly 2 °C	Focused on envelope level thermal performance
Huang et al. [50]	Solar thermal and heat storage integration in buildings	Building systems	Solar thermal systems, TES, PCM heat storage walls	Highlighted enhanced thermal regulation, energy self-sufficiency, and improved solar thermal utilization in buildings	Limited emphasis on urban-scale and network integration
Michailidis et al. [51]	MPC for smart buildings	Smart building systems	MPC, HVAC, electric vehicle (EV) charging, renewable integration and storage	Reported growing use of hybrid and multi-agent MPC frameworks for energy optimization	Lack of real-world deployment, and benchmark validation
Khdair et al. [52]	PCM integration in buildings	Building envelope level	PCM walls, floors, ceilings, windows, nano-enhanced PCMs	Reduced peak indoor temperatures by up to 5.8 °C and HVAC energy-use by 15–42%	Limited discussion on smart grids and large-scale
Kang et al. [53]	Bioarchitected PCM composites for zero energy buildings	Building material-level	Bio-based PCMs, thermal storage composites	Emphasized scalable low-carbon building materials for net-zero buildings	Focused mainly on material innovation rather than integration
Melo et al. [54]	Off-grid industrial buildings in cold climates	Industrial building-level	PV, wind, thermal storage, hydrogen	Identified thermal storage as the most reliable heating strategy in cold climates	Focused only on cold-climate industrial buildings
The present review	Intelligent TES networks for net-zero tropical cities	Multi-scale: building, district, and urban systems	TES, AI, ML, IoT, smart grids, district cooling	Classifies 47 quantitative studies by validation level and TES-centrality; 78.7% are simulation-only; demonstrates TES potential for reducing peak cooling demand, improving grid stability, renewable integration, and urban resilience	Identifies challenges in scalability, interoperability, lifecycle sustainability, and real-time deployment; no validated multi-district intelligent TES network exists

The remainder of the paper is organized as follows. Section 2 describes the review methodology, the evidence-quality framework, and the governing equations and metrics used for quantitative comparison. Section 3 reviews TES technologies. Section 4 examines TES integration at building, district, and urban scales and consolidates the structured evidence table. Section 5 assesses AI and digital technologies. Section 6 consolidates applications, impacts, and case studies. Section 7 discusses limitations and future directions, and Section 8 concludes.

2. Research Methodology

2.1. Search Strategy and Study Selection

The literature selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework using the Scopus, Web of Science, and IEEE databases [55]. Two search strings were applied. The primary string combined the terms “artificial intelligence” and “thermal energy storage” and was run on 30 June 2026. A supplementary string was run to capture studies that use “machine learning, deep learning, reinforcement learning, predictive or intelligent control, demand response, thermal flexibility, district cooling, or aquifer, borehole, pit, ice, and PCM storage”. Table 2 lists the exact database-specific strings, search fields, Boolean operators, date limits, and record counts. The primary string returned 2960 records (Scopus 1684; Web of Science 912; IEEE Xplore 364), and the supplementary string returned 1487 records, giving 4447 records in total. Duplicate removal by DOI and normalized title matching eliminated 1655 records, leaving 2792 records for title and abstract screening. Filters for English language, publication years (2002–2026), journal articles and reviews, conference papers, book chapters, and final publication stage were then applied, and each abstract was checked for relevance to the review theme. Screening excluded 2471 records: 1612 addressed storage without a thermal component (battery, electrochemical, or hydrogen only), 598 contained no AI, ML, optimization, or intelligent control element, 187 fell outside the building, district, or urban context, and 74 were editorials, errata, notes, or non-English documents. Full texts of 321 reports were assessed. A further 180 were excluded because TES was peripheral to or absent from the system boundary (74), no quantified energy, cost, emission, or peak load metric was reported (41), methodological detail was insufficient to assign a validation level (33), the same dataset was reported elsewhere (12), or the full text was not accessible (20). This process resulted in 141 database-identified documents. Backward citation searching of the included reviews yielded 33 records, comprising foundational references on district heating and cooling, urban energy system definitions, and AI interpretability, as well as authoritative reports from the International Energy Agency and NITI Aayog. These records were screened with the same eligibility criteria and are identified in Figure 1. The final evidence base contains 174 documents: 52 reviews, 110 research articles, 2 conference papers, 3 books or book chapters, and 7 reports and guidelines. Nearly 61% of the selected documents were published during 2025–2026, indicating a rapidly evolving research domain.

Table 2. Database-specific search strings, fields, limits, and record counts (accessed 30 June 2026).

Database	Search Field	Primary String (Boolean)	Records	Supplementary String (Boolean)	Records	Limits Applied
Scopus	TITLE-ABS-KEY	("artificial intelligence" OR "AI") AND ("thermal energy storage" OR "thermal storage")	1684	("machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network" OR "predictive control" OR "intelligent control" OR "demand response" OR "thermal flexibility") AND ("thermal energy storage" OR "thermal storage" OR "phase change material" OR "district cooling" OR "district heating" OR "aquifer thermal" OR "borehole thermal" OR "pit thermal" OR "ice storage")	861	PUBYEAR 2002–2026; LANGUAGE English; DOCTYPE ar, re, cp, ch; PUBSTAGE final; SUBJAREA ENER, ENGI, COMP, DECI

Table 2. Cont.

Database	Search Field	Primary String (Boolean)	Records	Supplementary String (Boolean)	Records	Limits Applied
Web of Science Core Collection	TS (topic)	TS = ("artificial intelligence" OR AI) AND TS = ("thermal energy storage" OR "thermal storage")	912	TS = ("machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network *" OR "predictive control" OR "intelligent control" OR "demand response" OR "thermal flexibility") AND TS = ("thermal energy storage" OR "thermal storage" OR "phase change material *" OR "district cooling" OR "district heating" OR "aquifer thermal" OR "borehole thermal" OR "pit thermal" OR "ice storage")	471	PY 2002–2026; LA English; Article, Review, Proceedings Paper, Book Chapter; SCI-E, ESCI, CPCI-S
IEEE Xplore	Abstract, Title, Author keywords	("artificial intelligence" OR "AI") AND ("thermal energy storage" OR "thermal storage")	364	("machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network" OR "predictive control" OR "demand response") AND ("thermal energy storage" OR "thermal storage" OR "phase change material" OR "district cooling" OR "ice storage")	155	Year 2002–2026; Journals, Conferences, Early Access
Total			2960		1487	Identified 4447; duplicates 1655; screened 2792

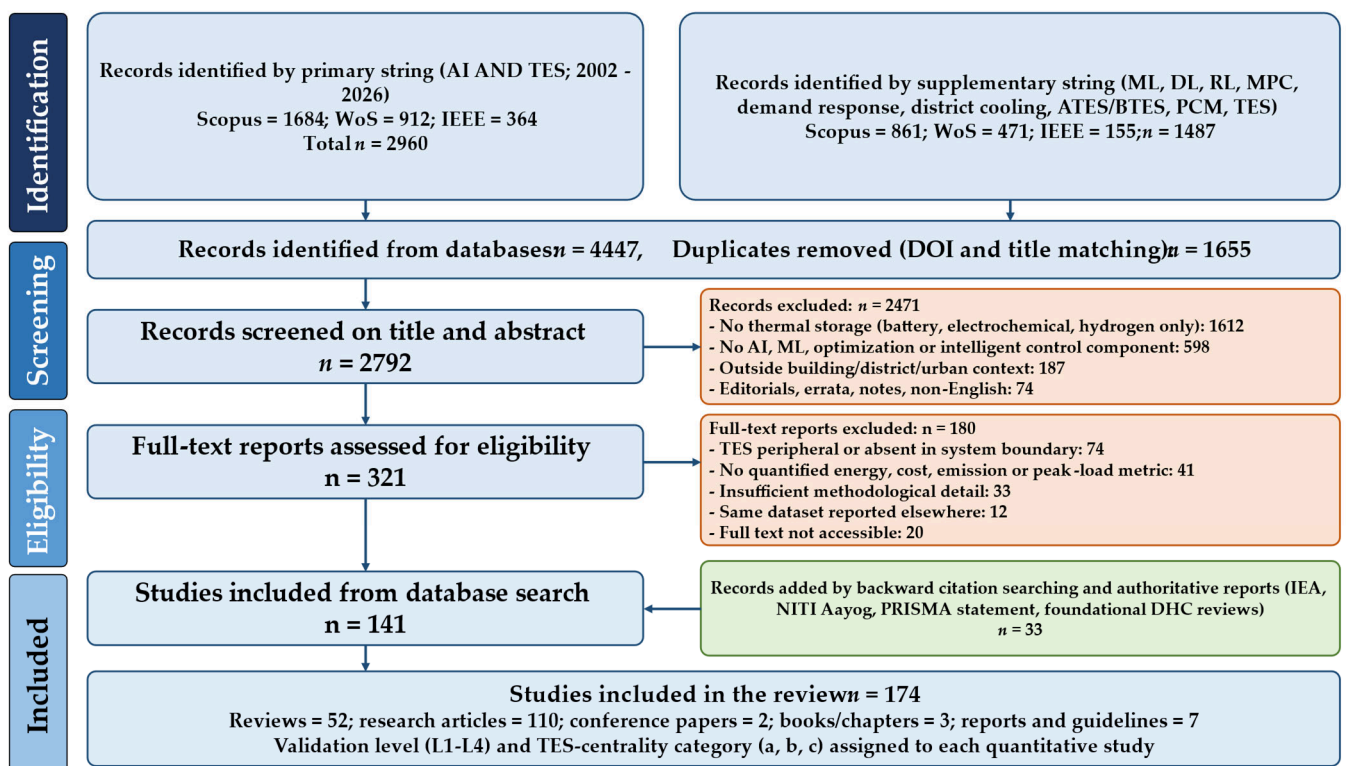


Figure 1. PRISMA 2020 flow diagram for the primary and supplementary searches, with exclusion counts and reasons at each stage.

The bibliometric profile of the included literature confirms that the field is young and geographically concentrated. Figure 2 shows the annual distribution of the 174 included records. Only 25 records (14.4%) were published before 2020, whereas 107 records (61.5%) appeared in 2025–2026. Figure 3 maps the records by the lead author's country. China (44 records, 25.3%) and India (18 records, 10.3%) lead, followed by the United States (12), the United Kingdom (10), Italy (9), and Germany (8). European countries together contribute 61 records (35.1%), but only 9 records (5.2%) originate from tropical countries other than India. The evidence base is therefore thinnest where cooling-driven demand growth is highest.

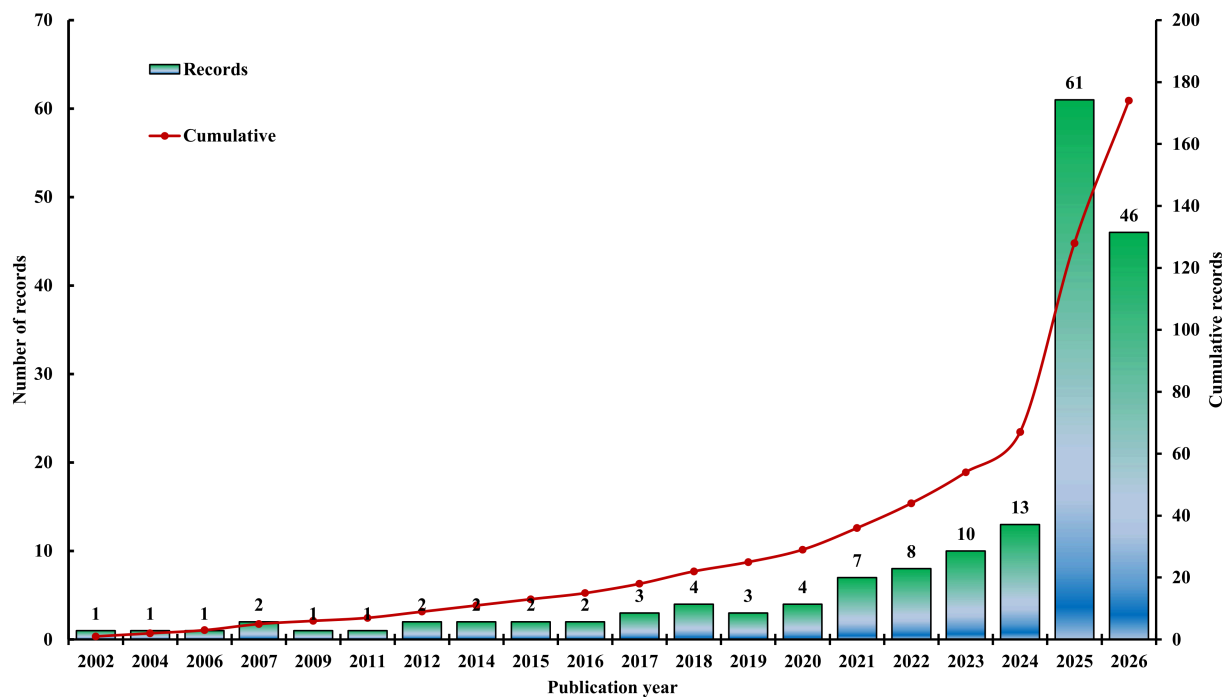


Figure 2. Annual distribution and cumulative count of the 174 records included in this review (2002 to June 2026).

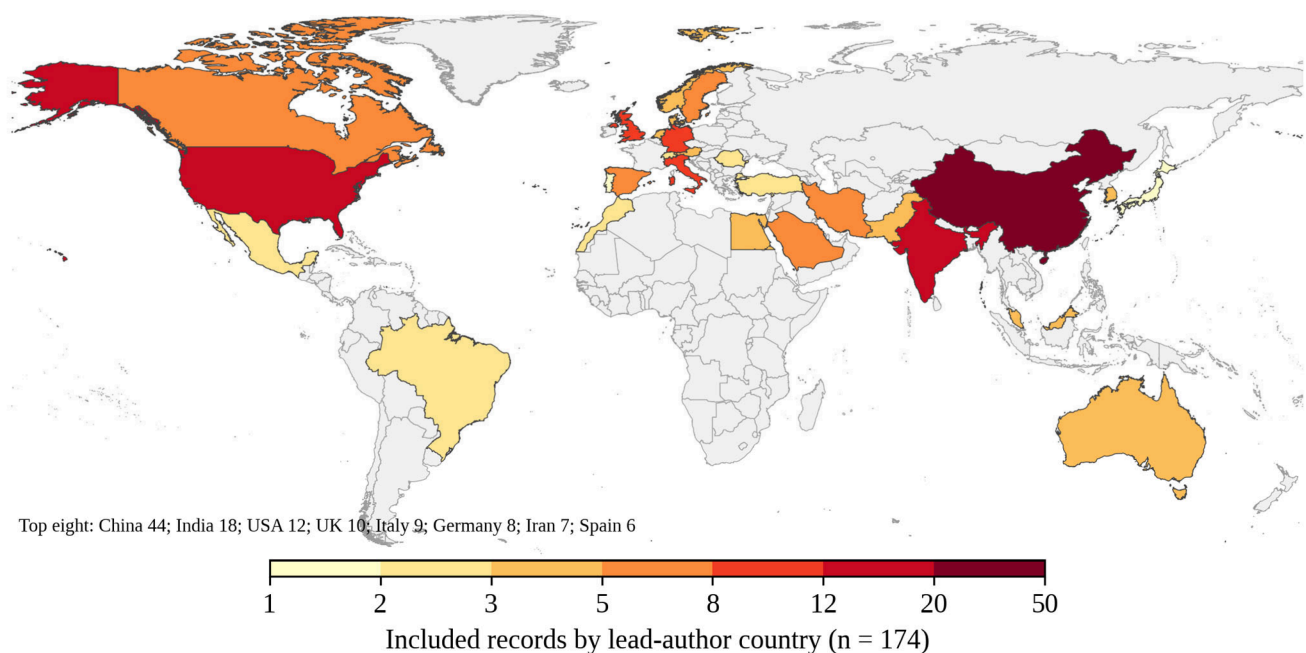


Figure 3. Geographic distribution of the included records by lead author country ($n = 174$).

The reviewed literature shows that advanced TES technologies, intelligent control algorithms, and integrated system architectures are converging. Yet several gaps remain. Most studies address individual TES technologies or building-scale applications, while few examine TES integration within city-scale thermal networks. The role of AI in optimizing distributed TES networks across urban infrastructure has not been comprehensively examined. Most studies also focus on developed regions, with limited attention to rapidly urbanizing tropical countries such as India, where demand patterns, infrastructure constraints, and climate differ substantially. Finally, conceptual frameworks that integrate TES technologies, renewable energy, AI-driven optimization, and smart urban infrastructure within a unified model for net-zero cities remain scarce. Figure 4 presents the conceptual framework of intelligent TES networks for net-zero energy cities that structures this review and links urban energy challenges, storage technologies, the digital intelligence layer, applications, and enabling frameworks.

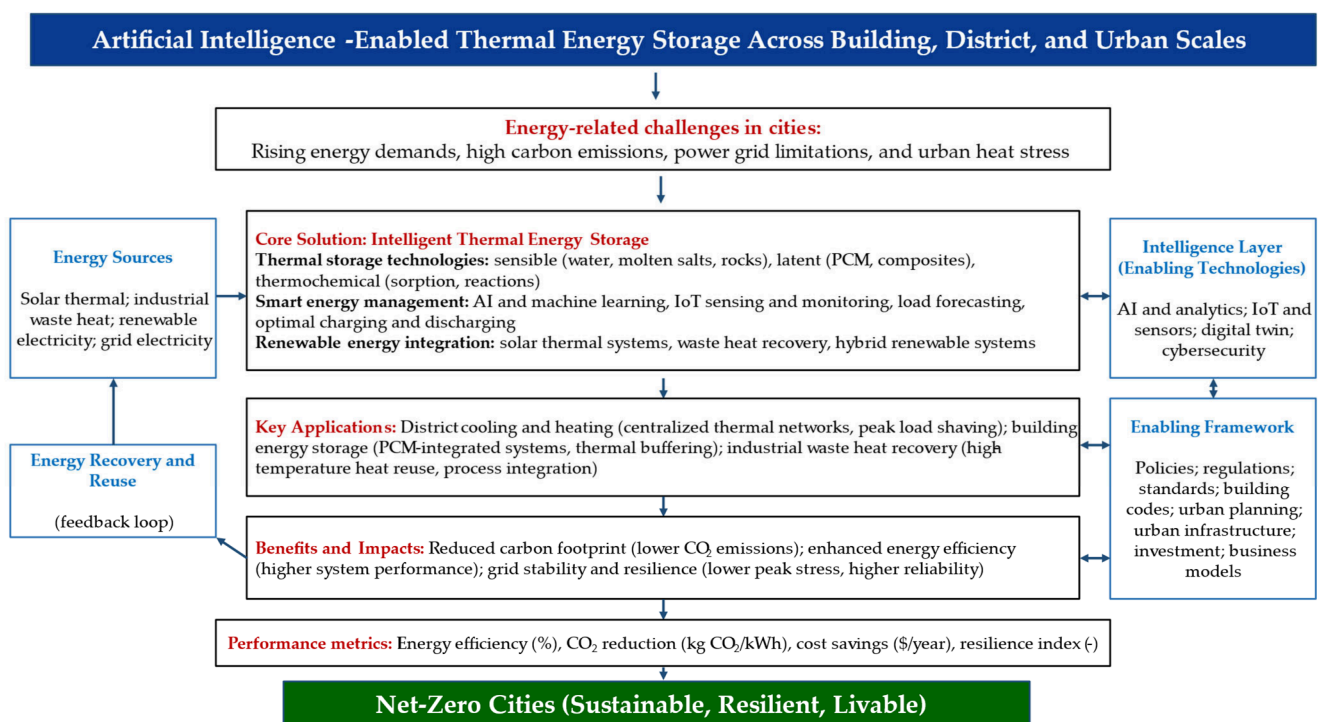


Figure 4. Conceptual framework of intelligent TES networks for net-zero energy cities.

2.2. Evidence-Quality Framework, TES-Centrality Categories, and Scale Criteria

No formal risk-of-bias instrument exists for engineering simulation and deployment studies. A transparent evidence-quality framework was therefore defined a priori and applied to every study reporting quantitative outcomes in energy, cost, emissions, peak load, or accuracy (Table 3). Validation level L1 denotes simulation-only studies, including optimization models and co-simulations without measured data. L2 denotes laboratory experiments, test rigs, or models calibrated against measured data from a real system. L3 denotes pilot or field demonstrations in which the intelligent controller operated a real building or network for a limited period. L4 denotes operational deployments with multi-year monitored data or fleet-level statistics. Each study was also assigned a TES-centrality category. Category (a) contains studies in which an AI, optimization, or control method directly operates or designs a TES asset and the reported outcome is attributable to that asset. Category (b) contains multi-energy systems in which TES is one of several storage components. Category (c) contains AI-based energy management studies without an explicit TES component that are cited only for methodological context. Studies that

report TES deployment without any intelligent component are labeled T. Two authors independently classified all studies. Initial agreement was 42 of 47 studies (89.4%) for validation level and 44 of 47 (93.6%) for centrality category; disagreements were resolved by discussion with a third author. Conclusions about AI performance in TES are drawn from category (a) studies, and the validation level is reported alongside every performance value in Sections 4–6. The scale criteria defined in Section 1.2 were applied in the same pass.

Table 3. Evidence-quality levels, TES-centrality categories, and scale criteria applied in this review.

Dimension	Class	Definition	Example Study	Count (<i>n</i> = 47)
Validation level	L1 Simulation only	Numerical, optimization, or co-simulation results without measured data from the studied system	Ma et al. [56]; Wang et al. [57]	37 (78.7%)
	L2 Laboratory or calibrated	Laboratory experiment, test rig, or model calibrated against measured data of a real system	Ye and Ding [58]; Serageldin et al. [59]	4 (8.5%)
	L3 Pilot or field	Intelligent controller operated a real building or network for a limited campaign	Svetozarevic et al. [60]; Xiong et al. [61]	2 (4.3%)
	L4 Operational	Multi-year monitored deployment or fleet-level operating statistics	Fleuchaus et al. [24]; Behzadi and Sadrizadeh [62]	4 (8.5%)
TES-centrality category	(a) Direct TES-AI	AI, optimization, or control method directly operates or designs the TES asset; outcome attributable to TES	Jin et al. [63]; Hemmatabady et al. [64]	18 (38.3%)
	(b) TES within multi-energy system	TES is one of several storage carriers (battery, hydrogen, EV) in the optimized system	Vetter et al. [65]; Khan et al. [66]	17 (36.2%)
	(c) AI energy management without explicit TES	Contextual evidence on method behavior; not used for TES performance conclusions	Monfaredi et al. [67]; Alotaibi [68]	9 (19.1%)
	TES deployment without AI	Operational or techno-economic TES evidence without an intelligent component	Dahash et al. [25]	3 (6.4%)
Scale	Building/component	Single building or component; one owner; 1 kWh _{th} to 1 MWh _{th}	Emami et al. [69]	31
	Building cluster	Several buildings sharing plant or storage; aggregator or community; 1–100 MWh _{th}	Vetter et al. [65]	8
	District	Network serving hundreds of buildings; utility operator; 100 MWh _{th} to 10 GWh _{th}	Wang et al. [57]	7
	City/urban	Coordinated TES assets across two or more districts, or municipal multi-energy model (labeled model if no physical coordination)	Monfaredi et al. [67] (model)	1 (model); 0 (deployed)

2.3. Governing Equations and Performance Metrics Used for Quantitative Comparison

The quantitative values synthesized in this review derive from a small set of governing relations and performance metrics. They are summarized here so that reported figures can be interpreted on a common basis. The stored energy in sensible, latent, and thermochemical storage follows Equations (1)–(3), where m is the storage mass, C_p the specific heat, L the latent heat, ΔH_r the reaction enthalpy per unit mass, and α the reacted fraction.

$$Q_{\text{sens}} = m c_p (T_2 - T_1) \quad (1)$$

$$Q_{\text{lat}} = m [c_{p,s}(T_m - T_1) + L + C_{p,l}(T_2 - T_m)] \quad (2)$$

$$Q_{\text{tcm}} = m \Delta H_r \alpha \quad (3)$$

Transient storage behavior is governed by energy conservation. For sensible storage, the heat-conduction form applies Equation (4); for latent storage, the enthalpy formulation absorbs the moving phase boundary Equation (5). Thermochemical storage couples the same energy balance to a reaction source term, Equation (6), in which the reacted fraction follows a simplified first-order kinetic law, Equation (7). The kinetic relation is a reaction rate expression, not a heat transfer equation.

$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) \quad (4)$$

$$\rho \frac{\partial H}{\partial t} = \nabla \cdot (k \nabla T), \quad H = \int c_p dT + L f_l \quad (5)$$

$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + \rho_s \Delta H_r \frac{\partial \alpha}{\partial t} \quad (6)$$

$$\frac{\partial \alpha}{\partial t} = k_r (1 - \alpha), \quad k_r = A \exp \left(-\frac{E_a}{R T} \right) \quad (7)$$

System-level performance is compared using the round-trip efficiency and volumetric energy density, as given in Equations (8) and (9), where Q_{dis} and Q_{ch} are the discharged and charged energies over a cycle, and V is the storage volume.

$$\eta_{\text{rt}} = \frac{Q_{\text{dis}}}{Q_{\text{ch}}} \times 100\% \quad (8)$$

$$e_v = \frac{Q_{\text{dis}}}{V} \quad (9)$$

Operational outcomes reported in Section 4 to Section 6 are normalized relative to a stated baseline. Energy savings, peak load reduction, and cost savings follow Equations (10)–(12), where the subscript ref denotes the baseline control strategy over the same evaluation period. Simple payback follows Equation (13).

$$\Delta E = \frac{E_{\text{ref}} - E_{\text{AI}}}{E_{\text{ref}}} \times 100\% \quad (10)$$

$$\Delta P = \frac{P_{\text{max,ref}} - P_{\text{max,AI}}}{P_{\text{max,ref}}} \times 100\% \quad (11)$$

$$\Delta C = \frac{C_{\text{ref}} - C_{\text{AI}}}{C_{\text{ref}}} \times 100\% \quad (12)$$

$$\text{PBP} = \frac{I_0}{C_{\text{ref}} - C_{\text{AI}}} \quad (13)$$

Forecasting accuracy is reported through the mean absolute error, root mean square error, and coefficient of determination, Equations (14)–(16), for n predicted values $\hat{y}_i$ against measurements y_i with mean $\bar{y}$.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (14)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (16)$$

Decision methods differ in the problem they solve. Model predictive and mixed-integer formulations minimize a cost functional over a horizon N subject to system dynamics and constraints, Equation (17), where u_k is the control vector (charging and discharging rates) and x_k is the state (storage level, temperatures). RL instead maximizes the expected discounted return of a policy π through the action-value function, Equation (18), with reward r_t (negative cost or discomfort) and discount factor γ . These formulations underlie the comparative scoring in Section 5.

$$\min_{u_0, \dots, u_{N-1}} \sum_{k=0}^{N-1} \left[c_k^\top u_k + \lambda \|x_k - x_k^{\text{ref}}\|^2 \right] \quad \text{s.t.} \quad x_{k+1} = f(x_k, u_k), \quad u_k \in \mathcal{U}, \quad x_k \in \mathcal{X} \quad (17)$$

$$Q^\pi(s, a) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t r_t \mid s_0 = s, a_0 = a \right] \quad (18)$$

3. TES Technologies

TES is a key enabling technology for sustainable UESs. TES allows excess thermal energy to be stored during low-demand periods and released during peak periods, improving energy efficiency and reducing electricity consumption. In urban environments, TES balances supply and demand, supports the integration of renewables, and improves building energy performance. TES also enables load shifting, productive use of waste heat, and thermal regulation of indoor spaces. TES technologies fall into three main categories: sensible heat storage, latent heat storage, and thermochemical storage. Figure 5 illustrates the operating principle of each category: a temperature rise in a stratified medium, a near-isothermal melting plateau, and a reversible endothermic-exothermic reaction pair that permits loss-free storage between charging and discharging. Figure 6 shows this classification, including the main advantages, disadvantages, example materials, and storage durations for each category.

Table 4 quantitatively compares the three categories, distinguishing material-level from system-level parameters and providing source-specific ranges. Energy density rises from 10–50 kWh/m³ for sensible storage to 150–500 kWh/m³ for thermochemical storage, while cycle stability and technical maturity fall in the same order. No single technology dominates: sensible storage offers maturity and low cost, latent storage offers compactness and near-isothermal operation, and thermochemical storage offers long-duration capability at high complexity.

3.1. Sensible Heat Storage

Sensible heat storage systems store thermal energy by raising the temperature of a storage medium without phase change. Water, molten salts, rocks, and concrete are commonly used for their high heat capacity and thermal stability. These systems are widely used in district heating networks, solar thermal plants, and industrial waste heat recovery (WHR). Comparative analyses of TES technologies show differences in energy density,

efficiency, operating temperature, and technology readiness that determine suitability for urban applications [70]. Sensible storage dominates district networks because of its maturity, low cost per kWh, and cycle stability above 10,000 cycles. Its main drawbacks are low energy density and large storage volumes, which constrain siting in dense urban areas.

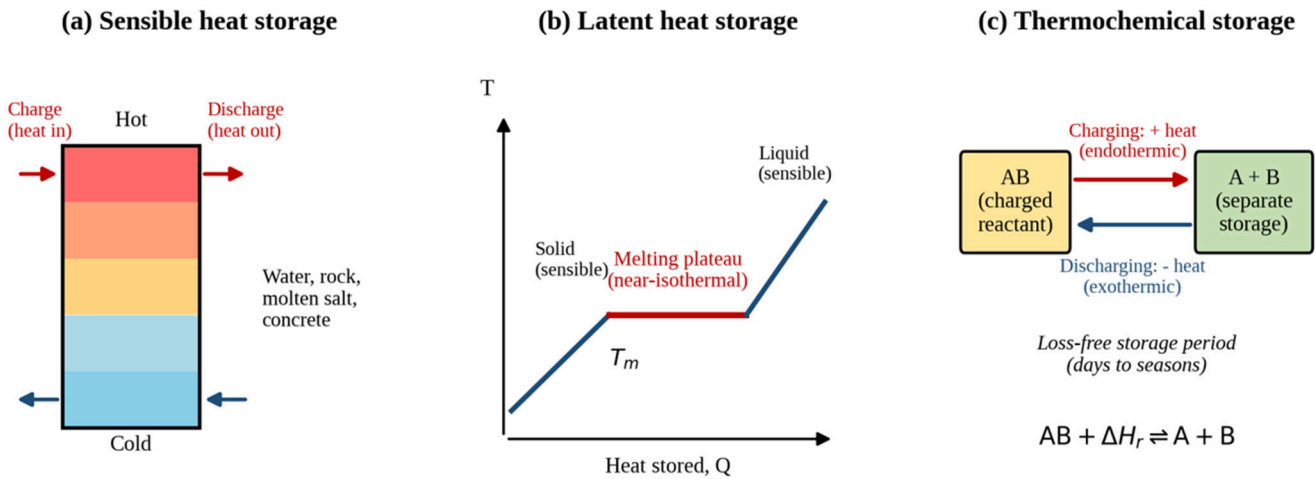


Figure 5. Operating principles of (a) sensible, (b) latent, and (c) thermochemical storage with the corresponding capacity relations, typical system-level energy densities, and cycle stabilities.

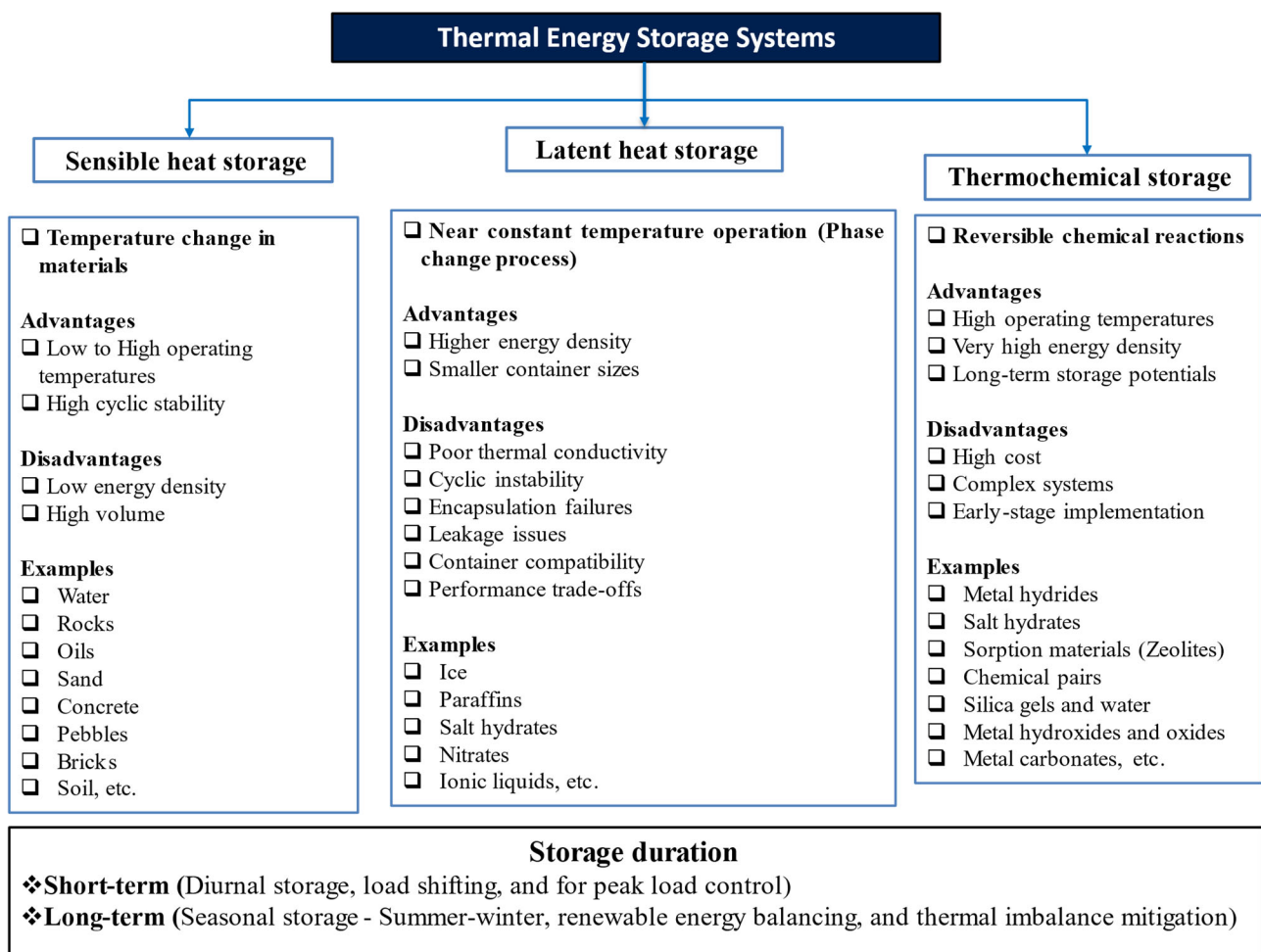


Figure 6. Major classifications of TES systems [15–17,20–22].

Table 4. Quantitative comparison of the major TES categories with material-level (M) and system-level (S) parameters and source-specific ranges [15,17,19,22,70,71].

Parameter	Level	Sensible Heat	Latent Heat	Thermochemical	Sources
Basic principle	-	Temperature rise	Phase change	Reversible reaction or sorption	[16,19]
Capacity relation	-	Equation (1)	Equation (2)	Equation (3)	Section 2.3
Specific heat, c_p (kJ/kg·K)	M	Water 4.18; rock and concrete 0.8–1.0; molten salt 1.5	Paraffins 2.0–2.5; salt hydrates 1.5–3.5	Not dominant	[19,70]
Latent heat, L (kJ/kg)	M	-	Paraffins 150–250; salt hydrates 100–300	-	[70,71]
Reaction enthalpy, ΔH_r (kJ/kg)	M	-	-	Salt hydrates 500–1500; hydroxides and carbonates 1000–3000	[22]
Density, ρ (kg/m ³)	M	Water 1000; rock 2200–2600; molten salt 1800–1900	700–2000	1000–3000	[17,19]
Thermal conductivity, k (W/m·K)	M	Water 0.6; concrete 1–2; rock 2–5	0.2–0.6	0.1–1.5	[17,70]
Operating temperature, T (°C)	S	Water tanks 20–95; molten salt 290–565	Building PCMs 18–28; industrial PCMs up to 800	Salt hydrates 50–150; oxides and carbonates 400–1200	[15,22,71]
Energy density (kWh/m ³)	S	10–50 (water at $\Delta T = 10$ –40 K)	50–150 (PCM modules)	150–500 material; 100–250 reactor systems	[15,17,22]
Thermal expansion	M	10^{-4} – 10^{-3} K ⁻¹	High during phase change (5–15% volume change)	Reaction-dependent (up to 20%)	[19,71]
Transient energy balance	-	Equation (4)	Equation (5)	Equation (6)	Section 2.3
Reaction kinetics (simplified first order)	M	-	-	Equation (7)	[22]
Round-trip efficiency (%)	S	50–90	60–95	40–85	[15,17]
Cycle stability (cycles)	M/S	>10,000	500–5000 (commercial PCMs up to 10,000)	100–2000	[15,22,71]
Technology readiness level	S	9	6–9	3–6	[15,17]
Encapsulation	-	Not required	Micro/macro encapsulation	Reactor-based containment	[71]
Container compatibility	-	Corrosion with molten salts	Corrosion and leakage issues	High chemical compatibility required	[19,22]
System complexity	S	Low	Medium	High	[15]

Table 4. Cont.

Parameter	Level	Sensible Heat	Latent Heat	Thermochemical	Sources
Typical scale	S	Large (MW–GW thermal)	Medium (kW–MW)	Pilot-industrial	[17]
Applications	S	District heating	Buildings, HVAC, solar storage	Seasonal storage, hydrogen systems, long-term storage	[15,17]

3.2. Latent Heat Storage

Latent heat storage uses PCMs to store energy during phase transitions, typically between solid and liquid states. PCMs absorb large amounts of heat during melting and release it during solidification, enabling higher storage density and stable operating temperatures [71]. PCMs are classified into organic, inorganic, and eutectic materials. Organic PCMs such as paraffin offer chemical stability and non-corrosiveness, whereas inorganic PCMs such as salt hydrates provide higher thermal conductivity and storage capacity [72]. PCM-based systems are widely used for building thermal regulation and cooling load management [73]. Their main limitations are low thermal conductivity (0.2–0.6 W/m·K), volume change of 5–15% during phase change, encapsulation failures, and cycle degradation.

Recent studies address these limitations through advanced composites, and Table 5 compares their quantified gains against the baseline limitations. Bu et al. [74] reviewed porous, shape-stabilized composite PCMs produced via vacuum impregnation, chemical grafting, and electrospinning, in which biomass-derived scaffolds enhanced conductivity and structural stability while retaining high latent heat. Tang et al. [75] developed PCM-hemp concrete with graphene oxide additives that increased latent heat capacity by 10% and thermal conductivity by 8.6%, yielding a potential 25% reduction in building energy consumption but a 55% loss in compressive strength. Dou et al. [76] improved microcapsule PCM composites with silane coupling agents and TiO₂, increasing the tensile strength by 23.6% and the rupture strength of the hybrid microcapsules by 105.2%. Liu et al. [77] reported cellulose-based phase change gels with switchable stiffness (21.87 to 5.37 MPa) and latent heat of 128.26 J/g. Gardner and Wang [78] introduced statistical frameworks that reduced parameter-estimation bias in nucleation during supercooling storage, thereby improving the predictive reliability of TES heat exchanger design.

Across these studies, conductivity gains of 8.6–28.8% and mechanical gains of 23.6–105.2% are consistently traded against latent heat or strength penalties of 10–55%, and all remain at the L2 laboratory validation stage. These material gains remain laboratory-scale, and their durability and manufacturability at network scale are unproven.

3.3. Thermochemical Storage

Thermochemical storage systems store heat through reversible chemical reactions or sorption processes. They offer the highest storage capacity (150–500 kWh/m³) and are well-suited to long-duration or seasonal storage, but entail greater system complexity, limited cycle stability (100–2000 cycles), and higher capital costs [22]. Thermochemical storage is being explored for seasonal TES, which could significantly improve long-term energy management in UESs. Current deployments remain at the pilot and demonstration scales, corresponding to technology readiness levels of 3 to 6, and none of the thermochemical studies in this review exceed validation level L2.

Table 5. Recent material- and component-level TES studies: reported gains, penalties, and validation level.

Reference	TES Category	Innovation	Quantified Gain	Reported Penalty or Limit	Level
Mohammed et al. [35]	Latent (nano-PCM)	Al ₂ O ₃ and CuO nanoparticles in PCMs and nanofluids	Thermal conductivity +28.8%; ANN/particle swarm optimization (PSO) accuracy >97%	Nanoparticle settling; cost	L2
Li et al. [39]	Thermochemical (sorption)	ANN surrogate with multi-population GA	Prediction error <1%; optimal pressure 5.2–8.7 bar	Simulation-based design	L1
Bu et al. [74]	Latent (form-stable)	Porous biomass scaffolds by impregnation, grafting, electrospinning	Higher conductivity and shape stability at retained latent heat	Scale-up unproven	L2
Tang et al. [75]	Latent (PCM concrete)	Graphene oxide PCM-hemp concrete	Latent heat +10%; conductivity +8.6%; building energy –25% (simulated)	Compressive strength –55%	L2
Dou et al. [76]	Latent (microcapsules)	Silane coupling and TiO ₂ reinforcement	Tensile strength +23.6%; rupture strength +105.2%	Added processing steps	L2
Liu et al. [77]	Latent (gel)	Cellulose phase change gel with switchable stiffness	Latent heat 128.26 J/g; stiffness 21.87 to 5.37 MPa	Low-temperature range only	L2
Gardner and Wang [78]	Latent (ice)	Statistical nucleation-rate estimation for supercooled water	Reduced estimation bias in heat exchanger design	Model-level result	L1
Spietz et al. [22]	Thermochemical (salt hydrates)	Review of salt-hydrate reactors	Energy density 150–500 kWh/m ³ ; seasonal capability	Cycle stability 100–2000; TRL 3–6	Review
Montanari et al. [79]	Latent (bio-based)	Transparent wood PCM composite	Latent heat 89 J/g; environmental impact –39%	Optical and mechanical trade-offs	L2

4. TES Integration Across Building, District, and Urban Scales

Energy systems evolve bottom-up, from single buildings to building clusters, district networks, and finally integrated UESs. At the building-level, intelligent energy management, renewable integration, and TES improve efficiency and flexibility. District thermal networks then interconnect these systems, enabling energy sharing, WHR, and coordinated operation. Aggregation, optimization, and digital integration further enhance performance at the city-scale, supported by policy, interoperability, and stakeholder engagement. Social acceptance is a precondition at every scale. In a survey of 673 rural households in Romania, local conditions were the strongest predictor of willingness to adopt renewable heating (standardized $\beta = 0.437$; adjusted $R^2 = 0.347$), and 59.7% of female respondents supported the technology, indicating that technical performance alone does not secure uptake [80]. Table 6 maps typical systems, TES technologies, capacities, applications, and technical considerations across these five scales and frames the structure of this section. Figure 7 shows the corresponding integration architecture, in which TES assets are aggregated bottom-up while price, carbon, and grid signals propagate top-down. Each subsection

concludes with the validation level and TES-centrality category for the cited studies, and Section 4.4 consolidates all quantitative evidence into a single structured table.

Table 6. TES systems, capacities, and applications from building-level to regional level [23–25,81–83].

Aspect	Building-Level (Single Building)	Building Cluster	District Level (District Heating/Cooling)	City/Urban-Scale	Regional/National Scale
Typical systems	HVAC systems; domestic hot-water; building envelopes (PCM walls); heat pumps; solar thermal	Centralized HVAC plants; shared thermal networks; solar thermal fields; WHR	District heating and cooling; industrial WHR; large solar thermal plants; geothermal systems	Urban energy hubs; multi-energy systems (heat, power, gas); large-scale solar and industrial integration	Inter-regional heat networks; large-scale renewable integration; national storage reserves; sector coupling
TES technologies	PCM; water tanks; small-scale thermochemical	Water tanks; PCM; borehole TES	Large water or molten salt tanks; borehole TES; aquifer TES; PCM	Aquifer TES; rock caverns; pit storage; thermochemical storage; molten salt	Underground TES (aquifer, caverns); thermochemical; seasonal storage
Capacity	1 kWh _{th} –1 MWh _{th}	1 MWh _{th} –100 MWh _{th}	100 MWh _{th} –10 GWh _{th}	10 GWh _{th} –1 TWh _{th}	>1 TWh _{th}
Coordinated TES assets and decision-maker	One asset; building owner	Several assets; aggregator or community	Tens to hundreds of connections; utility	Multiple districts; municipality and regulator	Multiple cities; national planning
Typical applications	Space heating and cooling; peak load reduction; comfort management	Load balancing among buildings; renewable integration; cost and energy savings	Seasonal storage; peak load management; renewable and waste heat utilization	Inter-seasonal energy balancing; energy security and resilience; net-zero cities	Long-duration storage; energy independence; climate and resource resilience
Key technical considerations	Compact size and fast response; integration with building management systems	Network integration; hydraulic balancing; control coordination	High storage density and efficiency; long-term performance; TES	System-wide optimization; policy, regulation, and economics; social impacts	Long-term sustainability; regulations and standards; large capital and high reliability
Highest validation level in this review	L3–L4 (<i>n</i> = 31)	L4 (<i>n</i> = 8)	L4 for ATES and pit storage; L1 for intelligent control (<i>n</i> = 7)	L1 model only (<i>n</i> = 1)	No quantitative study

Bottom-up aggregation of TES assets (left to right); top -down price, carbon and grid signals (right to left)

Quantitative evidence in this review: building 31 of 47 studies; cluster 8; district 7; urban 1 (model only)

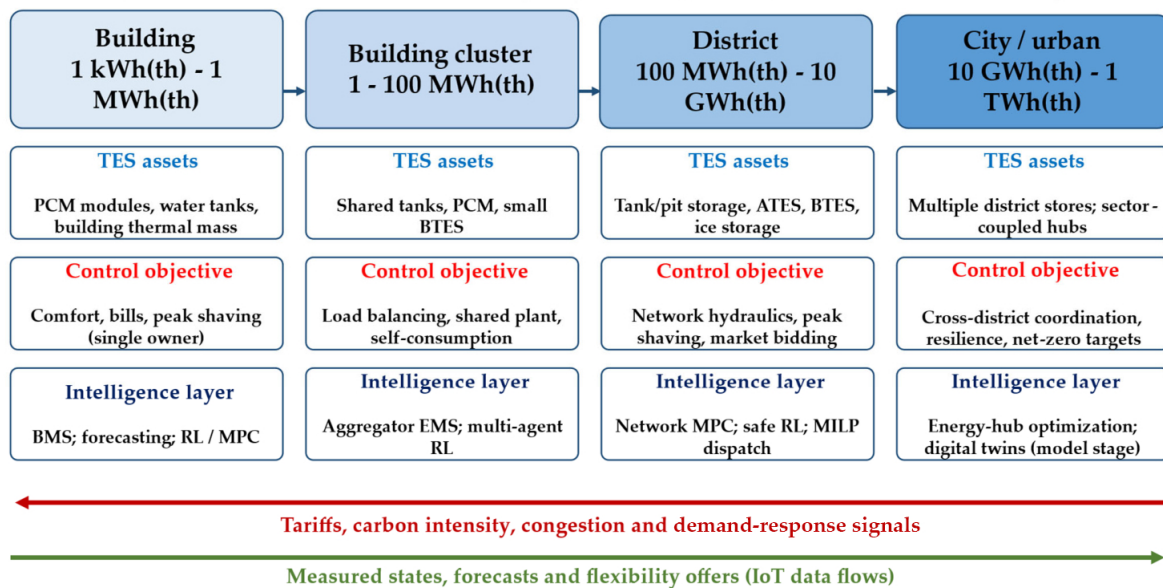


Figure 7. Multi-scale integration architecture for intelligent TES networks, showing TES assets, control objectives, and intelligence layers at each scale and the bidirectional signal and data flows.

4.1. Building-Scale TES and Smart Buildings

Integrating RESs such as solar and wind is essential for net-zero cities, but their variability challenges grid stability and supply reliability. TES addresses these challenges by storing excess thermal energy during periods of high renewable output and releasing it during periods of high demand [84]. Solar thermal energy stored during the day can serve to heat or cool buildings at night, and industrial waste heat can be stored for later use [85]. TES also supports demand-side management by shifting thermal loads away from peak electricity periods [86]. When integrated with smart grids, TES responds dynamically to real-time prices and grid signals [87].

Building-scale studies provide the most mature quantified evidence. Svetozarevic et al. [60] applied deep RL to building energy management with EV batteries and thermal loads, achieving 17% energy savings, 19% higher comfort satisfaction, and 30% lower operational energy use in a real building deployment (L3, category b). Dengiz and Kleinebrahm [88] designed an imitation learning heat pump controller with underfloor storage that reduced electricity costs while requiring less computation time than conventional optimization (L1, a). Ye and Ding [58] introduced active PCM walls with water circulation, in which Transformer-LSTM models improved prediction accuracy by 13.6%, reduced MAE by 70.8%, and increased thermal regulation capacity by 21.1% (L2, a). Ma et al. [56] optimized combined cooling, heating, and power systems with PCM heat banks using genetic algorithms (GA)-BP neural networks, reducing primary energy consumption by 7.74×10^3 to 2.08×10^6 kWh across five climate zones (L1, a). Emami et al. [69] implemented IoT-based PCM control, reducing electricity consumption by 8.2% and emissions by 8.7% while maintaining indoor temperatures at 17–21 °C under dynamic pricing (L1, a).

Further building-level evidence is consistent in direction but heterogeneous in system boundaries. Salerno et al. [89] reduced heating costs by 35% and cooling costs by 97% through intelligent building design integration without an explicit TES component (L1, c). Ahmad and Khan [90] reduced energy costs by 20.5% and achieved 88.2% load-scheduling accuracy in smart buildings (L1, c). Wu et al. [91] reduced NZEB energy consumption by up to 39.7% across Chinese climates with prediction accuracies above 0.94 (L1, c). Elaouzy and El Fadar [92] reported energy savings of 43.1–64.3% with PCM integration and carbon payback of 0.40–0.67 years for solar TES (L1, a). Fiorotti et al. [93] achieved 66% cost reduction by optimizing load scheduling for ten devices (L1, b). Yip et al. [94] reported peak power reductions of up to 54% and 25% cost savings for grid-responsive buildings (L1, b). Liu et al. [95] combined hydrogen, battery, and thermal storage using deep RL, achieving up to a 62.9% cost reduction amid renewable intermittency (L1, b). Peng et al. [96] developed thermochromic storage windows with 69.9% optical modulation, indoor temperature reductions of up to 28 °C, and savings of 43.3 MJ/m². Maturo et al. [97] reported PCM-PVT storage of 186.3 Wh/K with a payback period near 13.5 years, and Park et al. [98] cut envelope energy use by 5–9% while reducing thermal bridge losses by 89.6%. Reviews of solar-assisted heat pumps [99] and building-integrated PVT systems [100] confirm improved efficiency through hybrid integration, although fewer than 15% of the latter studies address high-rise applications. Direct TES-AI studies at building-scale (category a, $n = 13$) report simulated energy savings of 8.2–64.3% and peak load reductions of 35.5%; the single field-validated intelligent controller reports 17% energy savings [60], and the single operational BTES case supplies 28.5% of building demand [62]. Cost reductions of 0.8–66% come almost entirely from category (b) and (c) studies in which battery, hydrogen, or appliance scheduling contributes to the savings. The aggregate range of 8–40% energy savings reported in earlier versions of this review therefore describes simulation outcomes under favorable tariff and data assumptions, not validated expectations. Most results

are derived from simulation; experimentally validated deployments, such as those in Svetozarevic et al. [60], remain the minority.

4.2. District Heating and Cooling Networks with TES

District heating and cooling (DHC) is the established pathway for scaling TES beyond single buildings. District energy networks distribute thermal energy from centralized or distributed plants to many buildings, and their global research output has grown steadily [101,102]. Modern network concepts strengthen the role of storage. Fourth-generation district heating lowers supply temperatures to 30–70 °C, enabling renewable and waste heat sources and making water-based storage more effective [81]. Fifth-generation networks operate near ground temperature and exchange both heating and cooling among prosumers, with early European case networks demonstrating the concept [82]. TES in DHC serves four documented functions: daily peak shaving, seasonal balancing, network congestion relief, and market-based flexibility [83]. Control strategies that unlock this flexibility, including storage-aware scheduling and demand response, are reviewed by Vandermeulen et al. [26], who identify network thermal inertia itself as an underused storage resource.

Large sensible storage technologies are commercially proven at this scale. More than 2800 aquifer TES (ATES) systems operate worldwide, delivering over 2.5 TWh of heating and cooling per year with energy savings of 40–70% and payback periods of 2–10 years [24] (L4, T). Pit storage reaches a similar level of maturity in Denmark, where the Vojens system stores 203,000 m³ of hot water for solar district heating, and tank and pit costs fall below 0.5 EUR/kWh at large volumes [25] (L4, T). Borehole TES (BTES) integrates with district systems and heat pumps: a smart geothermal building system with BTES and district heating generated 120 kWh/m², reduced CO₂ intensity to 1.90 kg/MWh, and reached an eight-year payback [103] (L2, b). A deep green cooling installation in Uppsala supplied 28.5% of building energy demand from boreholes, delivering 3138 MWh of heating and cooling and avoiding 143.7 t of CO₂ [62] (L4, a). Hemmatabady et al. [64] showed that ANN-assisted optimization of solar-coupled BTES cut emissions by 60% relative to fossil systems at only 13% higher levelized cost (L1, a).

District cooling is the most relevant configuration for tropical cities, and intelligent operation at this scale is emerging. Wang et al. [57] achieved real-time optimization of an ice storage district cooling network with up to 619 nodes within milliseconds using safe deep RL (L1, a). Waste heat integration strengthens district economics: a techno-economic assessment of data centre WHR for district energy scored 0.78 in an analytical hierarchy evaluation and cut greenhouse gas emissions by 30% [104] (L1, b). District multi-energy configurations and their performance are systematically classified by Xu et al. [105]. At the district scale, therefore, the operational evidence (L4) concerns the passive or rule-based operation of ATES, BTES, and pit storage, whereas every intelligent control study remains at L1. The two evidence types have not yet been combined in a single monitored network. Nevertheless, validated district cooling studies incorporating TES in high-wet-bulb tropical climates remain scarce, and most of the quantified evidence for DHC still comes from European heating-dominated networks. This asymmetry is a central deployment barrier for the cities where cooling demand is growing fastest [8].

4.3. City-Scale Multi-Energy Systems and Smart Grids

City-scale integration couples thermal networks with electricity, gas, water, and transport infrastructure. Applying the scale criteria of Section 1.2 reclassifies most studies previously described as city-scale. Of the ten quantitative studies cited in this subsection, six address building clusters or single districts, three are urban-scale optimization models

without physical coordination of TES assets, and none report coordinated operation of distributed TES across multiple districts. Chen et al. [106] developed a residential energy hub integrating electricity, gas, solar, and thermal storage, using LSTM-based forecasting to reduce operating costs while maintaining comfort (district model, L1, b). Khan et al. [66] showed that shared electric, thermal, and hydrogen storage in multi-energy microgrids reduced total costs by 0.8% and emissions by 5.3% under mixed integer linear programming (MILP) (building cluster, L1, b). Monfaredi et al. [67] reduced operating costs by 2.96–4.62% and emissions by 4.68–6.03% in combined electricity and gas networks using adaptive PSO (urban model, L1, c). Wang et al. [107] demonstrated that equivalent storage modeling improves reliability assessment of urban multi-energy systems while reducing computational burden. Kazemi et al. [108] implemented cloud-based MPC with Kubernetes scalability for multi-carrier home energy management, and Ceja-Espinosa et al. [109] cut operational costs by 63% and computation by 70% in cooperative multi-microgrid networks (building cluster, L1, c). Electrification compounds the coordination challenge: heat pumps and EV charging could add 102 GW and 96 GW of peak load in Germany by 2045, reinforcing the need for flexible storage [110].

Digital coordination at this scale introduces new vulnerabilities. Tavangar Rizi et al. [111] showed that cyber-attacks on smart energy hubs with electrical and thermal storage increased peak electric load by 17.4%, while support vector machine detection reached 91.67% classification accuracy (L1, b). In water-energy nexus systems, false data injection altered electricity demand by 2.3–21.5% and water demand by 6.3–21.5%, and LSTM-ResNet correction reduced reconstruction errors to 10.3% for power and 3.2% for water [112]. Repurposed infrastructure offers city-scale storage opportunities: abandoned mines converted into integrated energy hubs provided 2.22×10^6 kWh of storage and 6400 kW of cooling, achieving 80.6% carbon reduction and 99.3% energy self-sufficiency [113] (district, L1, b). Kröger et al. [110] and Grubler et al. [114] both indicate that such sector coupling, rather than isolated technologies, drives deep urban decarbonization. Overall, city-scale studies remain dominated by simulation and optimization models, and the claim that validated city-scale intelligent TES networks are lacking rests on the absence of any L2–L4 study that coordinates TES assets across two or more districts.

4.4. Structured Evidence Table and Cross-Scale Synthesis

Table 7 consolidates the 47 quantitative studies supporting the performance claims in this review. Each row reports the TES type, scale, climate or location, baseline or comparison strategy, evaluation period, metric and value, validation level, and TES-centrality category. Three patterns emerge. First, 31 of 47 studies (66.0%) are building-scale or component-scale, 8 (17.0%) address building clusters, 7 (14.9%) address districts, and a single urban-scale model exists. Second, 37 studies (78.7%) are simulation-only, 4 (8.5%) are laboratory or calibrated studies, 2 (4.3%) are field demonstrations, and 4 (8.5%) are operational; of the four operational cases, only one [62] includes an intelligent control layer on a TES asset. Third, the evaluation baselines differ: 29 studies compare against rule-based or fixed-schedule control, 9 against a no-storage reference, 5 against another optimization method, and 4 against measured operation, so percentage savings are not additive or directly comparable across rows. Climate coverage is also uneven. Seven studies (14.9%) are set in tropical or subtropical climates, and only two of these, an on-site demand response experiment [61] and a solar dryer digital twin [115], exceed validation level L1. Because of this heterogeneity, the remainder of this review reports performance ranges only within a stated category and validation level, and no range in this review should be read as a general performance expectation. Figure 8 shows the distribution of the 47 quantitative studies by validation level across system scales and across TES-centrality categories.

Table 7. Structured evidence table of quantitative studies by scale (L1–L4 validation level; a, b, c, T centrality category).

Study	TES Type	Scale	Climate/Location	Baseline	Evaluation Period	Metric: Value	Level	Category
Li et al. [39]	Solid-gas sorption TES	Component	Not applicable	Physical model	Design optimization	ANN prediction error: <1%	L1	a
Liu et al. [44]	None explicit (building thermal flexibility)	Building	Not specified (China)	Conventional MPC	Simulation	Energy consumption: −12.1%	L1	c
Svetozarevic et al. [60]	Room thermal mass (hydronic heating) + EV battery	Building (single zone)	Temperate (Switzerland)	Industry rule-based controller	Weeks of experiments	Heating energy: −17%	L3	b
Dengiz and Kleinebrahm [88]	Underfloor heating thermal mass with heat pump	Building	Temperate (Germany)	Conventional optimization/heuristic	Annual simulation	Electricity cost: Lower cost at reduced computation time	L1	a
Ye and Ding [58]	Active PCM wall with water circulation	Building component	Laboratory (UK)	LSTM and shallow learners	Test rig dataset	Prediction accuracy/MAE: +13.6%/−70.8%	L2	a
Ma et al. [56]	PCM heat bank in CCHP	Building	Five Chinese climate zones	CCHP without PCM	Annual simulation	Primary energy: -7.74×10^3 to -2.08×10^6 kWh	L1	a
Emami et al. [69]	Paraffin PCM in building envelope	Building	Temperate (London)	No PCM, no demand-side management	Annual simulation	Electricity/emissions: −8.2%/−8.7%	L1	a
Salerno et al. [89]	None explicit (generic EMS)	Building	Not specified	Fixed schedules	Daily simulation	Heating/cooling cost: −35%/−97%	L1	c
Ahmad and Khan [90]	None explicit (DER sizing)	Building	Not specified	Unscheduled operation	Daily simulation	Energy cost: −20.5%	L1	c
Wu et al. [91]	None explicit (NZEB design)	Building	Four Chinese climates	Reference design	Annual simulation	Energy consumption: up to −39.7%	L1	c
Elaouzy and El Fadar [92]	PCM and solar TES	Building	Six Moroccan climates	Building without storage	Annual simulation	Energy savings: 43.1–64.3%	L1	a
Fiorotti et al. [93]	Hot-water tank with PVT	Building	Subtropical (Brazil)	Unscheduled loads	Day-ahead simulation	Energy cost: −66%	L1	b
Yip et al. [94]	Thermal mass with BIPV/T	Building	Cold (Canada)	Non-flexible archetype	Annual simulation	Peak power/cost: −54%/−25%	L1	b
Liu et al. [95]	Heat storage with hydrogen and battery	Building	Not specified	Rule-based HEMS	Simulation episodes	Operating cost: up to −62.9%	L1	b
Maturo et al. [97]	PCM with PVT collectors	Building	Cold (Canada)	No storage	Annual simulation	Storage capacity/payback: 186.3 Wh/K; 13.5 years	L1	a
Behzadi et al. [103]	BTES with district heating	Building	Cold (Sweden)	District heating only	Annual model calibrated to measured data	CO ₂ intensity/payback: 1.90 kg/MWh; 8 years	L2	b
Cetina-Quinones et al. [115]	Sensible storage in solar dryer	Component	Tropical (Mexico)	Measured dryer data	Experimental campaign	R2 of digital twin: 0.9896	L2	a
Du et al. [116]	TES in solar-assisted hotel system	Building	Cold semi-arid (Xi'an)	Grid-based supply	Annual simulation	CO ₂ emissions: −60.86%	L1	b
Abuhussain [117]	Adaptive walls with thermal buffering	Building	Hot-arid (Saudi Arabia)	Static envelope	Annual simulation	Energy/carbon/peak: −36.3%/−40.8%/−31.8%	L1	b
Xiong et al. [61]	Active TES air-conditioning	Building	Subtropical (China)	Conventional control	On-site experiments	Demand response verified: Load shift achieved on-site	L3	a

Table 7. Cont.

Study	TES Type	Scale	Climate/Location	Baseline	Evaluation Period	Metric: Value	Level	Category
Alfaro-Lopez et al. [118]	Cold TES for residential cooling	Building	Mediterranean (Spain)	No storage	Stochastic annual simulation	Electricity/cost: up to −14.5%/−42.3%	L1	T
Lal et al. [119]	TES in solar LiBr absorption cooling	Building	Tropical (India)	Conventional control	Simulation	Collector efficiency/coefficient of performance (COP): +0.9–1.2%/+9.5–15%	L1	a
Gholami et al. [120]	Sorption TES with battery in PV greenhouse	Building	Not specified (Australia)	Battery only	Annual simulation	Energy dependency/battery cycling: −19.2%/−30%	L1	a
Wang et al. [121]	Active TES in grid-interactive building	Building	Not specified (China)	No flexibility dispatch	Daily simulation	Average load shift: 74% (active TES 50.8%)	L1	a
Mulani and Ling [122]	Water-heating as TES with PV and battery	Building	Tropical (Malaysia)	Standard tariff/sizing	Lifecycle simulation	Payback change: −17 to −18% (tariff); −39 to −41% (sizing)	L1	b
Jin et al. [63]	Bio-based PCM with predictive control	Building	Hot (extreme heat case)	Conventional control	Simulation episodes	Cost/peak load: −44.3%/−35.5%	L1	a
Serageldin et al. [59]	Hybrid TES (geothermal, solar thermal, district)	Building	Temperate (Austria)	Measured school data	Annual calibration	Model error (MPE/MAE): 12.65%/14.03%	L2	a
Esmailzadeh et al. [123]	Hybrid HVAC thermal buffering	Building	Variable climates	Fixed supervisory control	Annual simulation	Comfort compliance: 90%	L1	c
Hainoun et al. [124]	Geothermal and solar thermal with district interaction	Building	Temperate (Vienna)	Design targets	Multi-year monitoring	Self-supply/CO ₂ saving: 124%; 20.6 kg CO ₂ /m ²	L4	b
Ataya et al. [125]	Solar thermal with Organic Rankine Cycle (ORC) (cold TES)	Building	Hot (Egypt)	Conventional HVAC	Annual simulation	Energy saving: 97%	L1	b
Alotaibi [68]	None explicit (whole-building MPC)	Building	Hot-desert	Baseline schedule	Seasonal simulation	Electricity/peak: −14.0%/−24.9%	L1	c
Fleuchaus et al. [24]	ATES (>2800 systems)	Building cluster to district	Temperate (mostly Netherlands)	Conventional heating and cooling	Operational statistics	Energy savings/payback: 40–70%; 2–10 years	L4	T
Behzadi and Sadrizadeh [62]	BTES (deep green cooling)	Building cluster	Cold (Uppsala, Sweden)	Measured operation	Annual monitoring	Share of demand/CO ₂ avoided: 28.5%; 143.7 t CO ₂	L4	a
Hemmatbady et al. [64]	Solar-coupled BTES	Building cluster	Temperate (Germany)	Fossil reference system	Multi-year simulation	Emissions/levelized cost: −60%/+13%	L1	a
Khan et al. [66]	Shared thermal with electric and hydrogen storage	Building cluster (microgrid community)	Not specified	Individual storage	Day-ahead simulation	Cost/emissions: −0.8%/−5.3%	L1	b
Ceja-Espinosa et al. [109]	None explicit (multi-microgrid)	Building cluster (model)	Not specified	Centralized EMS	Daily simulation	Operating cost/computation: −63%/−70%	L1	c
Vetter et al. [65]	Hot-water TES in energy community	Building cluster	Temperate (Austria)	Rule-based operation	Annual simulation	Cost (MILP/deep RL): −10.06%/−8.78%	L1	b
Karkon et al. [126]	Hydronic storage with PVT and heat pumps	Building cluster	Cold (Norway)	Reference community	Annual simulation	Energy cost: −55%	L1	b
Valsan et al. [127]	None explicit (virtual energy exchange)	Building cluster (microgrids)	Tropical (India)	Independent microgrids	Annual simulation	Grid dependency: −30.7%	L1	c

Table 7. Cont.

Study	TES Type	Scale	Climate/Location	Baseline	Evaluation Period	Metric: Value	Level	Category
Dahash et al. [25]	Pit storage (203,000 m ³ , Vojens)	District	Cold (Denmark)	Not applicable	Operational	Storage cost: <0.5 EUR/kWh	L4	T
Wang et al. [57]	Ice storage district cooling (619 nodes)	District	Subtropical (China)	Model-based optimization	Daily dispatch simulation	Decision latency: Milliseconds; near-optimal cost	L1	a
Alawadhi et al. [104]	TES with data centre waste heat	District	Hot-arid (Gulf)	Conventional district supply	Techno-economic model	GHG emissions: −30%	L1	b
Chen et al. [106]	Thermal storage within energy hub	District (model)	Not specified	Non-predictive dispatch	Daily simulation	Operating cost: Reduced (not quantified)	L1	b
Tavangar Rizi et al. [111]	Electrical and thermal storage in energy hub	District (model)	Not specified	Attack-free operation	Simulated attack scenarios	Peak load under attack/detection accuracy: +17.4%/91.67%	L1	b
Zhang et al. [113]	Mine-based thermal and pumped storage	District	Not specified (China)	Grid supply	Annual simulation	Carbon reduction/self-sufficiency: −80.6%/99.3%	L1	b
Tian et al. [128]	Molten salt TES in solar cogeneration	Industrial site	Not specified (China)	Conventional supply	Annual simulation	Thermal efficiency/CO ₂ : 55.43%; −931.36 t/year	L1	a
Monfaredi et al. [67]	None explicit (electricity-gas networks)	Urban (model)	Not specified	Non-adaptive PSO	Daily simulation	Cost/emissions: −2.96 to −4.62%/−4.68 to −6.03%	L1	c

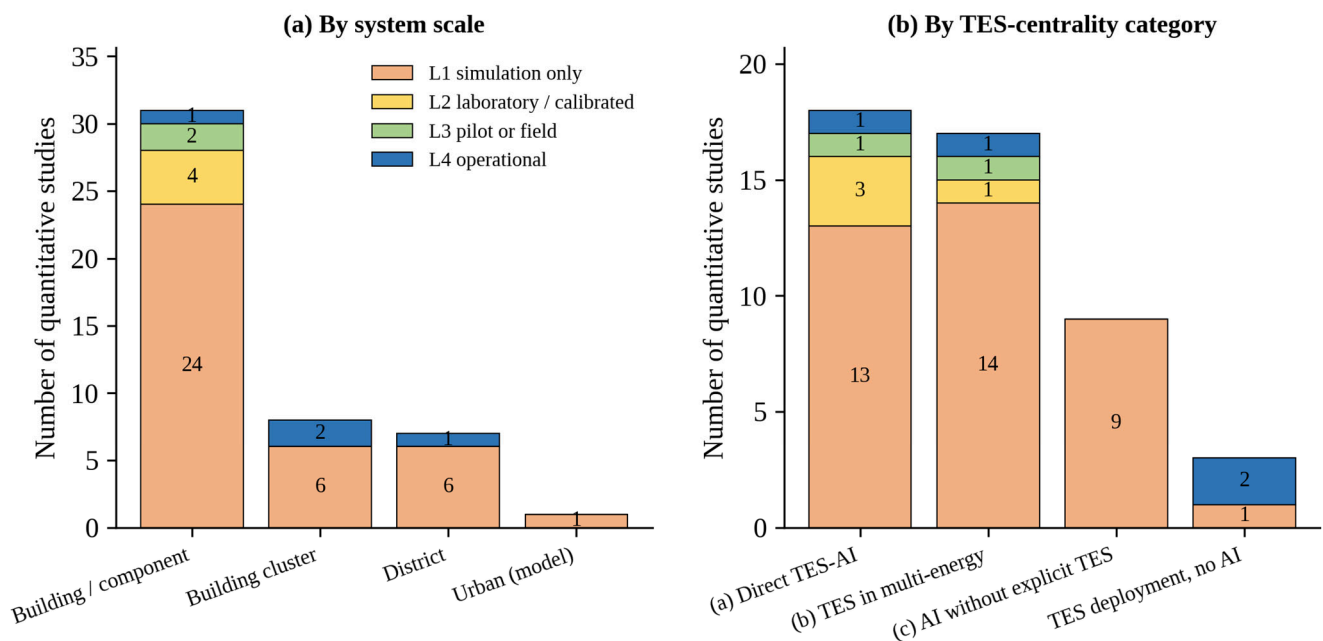


Figure 8. Distribution of the 47 quantitative studies by validation level: (a) across system scales and (b) across TES-centrality categories.

5. AI and Intelligent Digital Methods for TES Networks

5.1. AI and Intelligent Digital Methods Applied to TES

Smart energy management systems are central to TES operation in modern urban energy networks. Data-driven algorithms analyze historical consumption data to identify patterns in building thermal loads [129]. ANNs model nonlinear thermal processes and predict PCM behavior under varying conditions [130]. RL enables systems to learn operating strategies through interaction with the environment, allowing autonomous TES scheduling [131]. Evolutionary algorithms, such as GA and PSO, identify efficient operating strategies for TES networks [132]. Forecast-based optimization coordinates renewable generation and storage by predicting demand and weather [133]. Wu et al. [134] proposed the USFFNet architecture for battery state-of-charge estimation, reducing MAE by 68% at low temperatures and reaching 85% cross-domain accuracy with 94% reliability in a 1 MWh grid system; this battery study is cited for the architecture only (category c). Cetina-Quinones et al. [115] built an ANN digital twin of a solar dryer with sensible storage, achieving $R^2 = 0.9896$ and improving drying efficiency to 12.57%. Leonori et al. [135] used dynamic programming to improve grid energy fluctuation control by nearly 100% and stabilized daily energy exchange by a further 28%. Reviews of RL-based home energy management report improved efficiency and resilience but identify multi-agent coordination of storage as underexplored [136]. The methods in a closed-loop architecture: sensed data feed forecasting models, whose outputs enter a decision layer that issues charge and discharge commands to the physical TES system, with digital twins, cyber-resilience, and rule-based fallback as supporting functions (Figure 9). The methods differ in kind, and the taxonomy used here distinguishes four groups. Group (i) comprises AI and ML methods that learn mappings or policies from data (ANNs, LSTMs, Transformers, RL, SVMs, imitation learning, and hybrid deep networks). Group (ii) comprises optimization methods that search a decision space under an explicit objective (GA, PSO, MILP); these are not AI methods in themselves, and MILP in particular provides deterministic optimality guarantees. Group (iii) comprises control methods (MPC and its AI-assisted variants) that close the loop on a

plant model. Group (iv) comprises digital enabling technologies (AI-based digital twins) that integrate sensing, models, and analytics but are not algorithms in their own right.

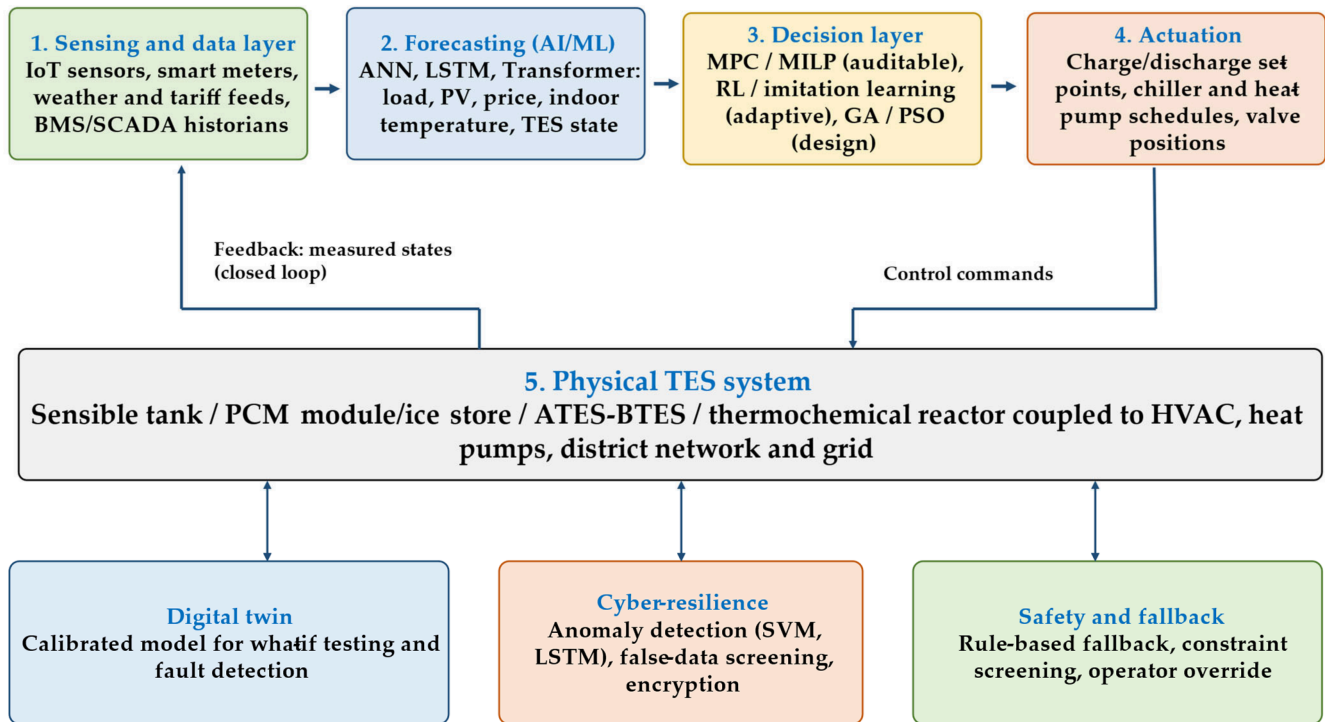


Figure 9. Closed-loop architecture of an intelligent TES system showing the sensing, forecasting, decision, and actuation layers, the physical storage system, and the supporting digital twin, cyber-resilience, and fallback functions.

Optimization and MPC approaches are classified as intelligent digital methods and are labeled AI-assisted only when a learning component is explicit. Table 8 summarizes 13 method families for TES applications, their strengths, inherent limitations, and representative quantified results, along with sources and validation levels.

5.2. Assessment Criteria and Comparative Evaluation

Comparisons of AI methods in the energy literature often rely on undefined qualitative labels. To avoid this, the thirteen method families in Table 8 are evaluated here against six explicitly defined criteria. Predictive accuracy denotes agreement between predicted and measured TES or load variables. Computational speed denotes online decision or inference latency at operational timescales. Interpretability denotes the degree to which operators can trace a decision to physical or logical causes. Data efficiency denotes performance attainable from limited historical or sensor data. Scalability denotes the ability to coordinate many distributed assets. Robustness denotes the retention of performance under distribution shift, such as weather extremes or changes in demand patterns.

Table 8. AI and intelligent digital methods for intelligent TES networks: group, applications, strengths, limitations, and reported performance with validation level.

Group	Method	TES Applications	Strengths	Limitations	Representative Reported Performance (Level)
(i) AI/ML	ANN	PCM modeling, building heat transfer, BTES design	Fast inference; nonlinear mapping	Deterministic outputs; retraining needed under new conditions	Prediction error below 1% [39] (L1); $R^2 = 0.9896$ [115] (L2)

Table 8. Cont.

Group	Method	TES Applications	Strengths	Limitations	Representative Reported Performance (Level)
(i) AI/ML	LSTM	Load forecasting, renewable-TES coordination	Temporal memory; suits streaming data	High data demand; low interpretability	Reduced hub operating costs [106] (L1); reconstruction error 10.3% after attack correction [112] (L1)
(i) AI/ML	Transformer/Transformer-LSTM	Multi-energy forecasting, flexible envelopes	Attention over long sequences	Very high data and computing demand	Accuracy +13.6%; MAE reduced 70.8% [58] (L2)
(i) AI/ML	RL/deep RL	TES scheduling, demand response, district cooling control	Adaptive model-free control; millisecond decisions after training	Sample inefficiency; unsafe exploration; opaque policies	17% energy savings [60] (L3); 12.1% consumption cut [44] (L1); 619-node district control in milliseconds [57] (L1)
(i) AI/ML	SVM (RBF)	Fault and anomaly detection	Effective with moderate data	Limited scalability to large networks	91.67% attack classification accuracy [111] (L1)
(i) AI/ML	Imitation learning (PSC-ANN)	Heat pump and TES control	Fast, stable, expert-informed policies	Bounded by expert policy quality	Lower cost and faster computation than optimization [88] (L1)
(i) AI/ML	Hybrid deep learning (USFFNet, LSTM-ResNet)	Storage state estimation, anomaly correction	Multi-scale feature fusion; deviation flagging	High computing and data demand	Error down 68% at low-temperature; 94% reliability [134] (L2, battery); errors 3–10% [112] (L1)
(i) AI/ML	Hybrid AI-metaheuristic (GA-BP, ANN-GA, ANN-grey wolf)	Multi-energy systems, design optimization	Combines prediction and optimization	Complex tuning; error propagation	Primary energy cut up to 2.08×10^6 kWh [56] (L1); CO ₂ –60.86% [116] (L1)
(ii) Optimization	Genetic algorithm	TES system design and sizing	Global gradient-free search	Offline use; slow convergence	Up to 39.7% energy reduction in NZEB design [91] (L1)
(ii) Optimization	PSO	Multi-energy operational optimization	Fast convergence; simple tuning	Premature convergence risk	Costs down 2.96–4.62%; emissions down 4.68–6.03% [67] (L1)
(ii) Optimization	MILP	Energy hub and storage scheduling	Optimality guarantees; transparent constraints	Linearization error; scaling limits	10.06% cost reduction [65] (L1); costs down 0.8%, emissions down 5.3% [66] (L1)
(iii) Control	MPC (including AI-assisted MPC)	HVAC and TES set-point control, hierarchical scheduling	Constraint handling; physics-based plant model	Model identification effort; forecast dependence	Energy –12.1% with RL-tuned MPC [44] (L1); electricity –14.0%, peak –24.9% [68] (L1)
(iv) Digital enabling	Digital twin (AI-based)	Real-time TES monitoring and scheduling	Predictive what-if simulation	Sensor dependence; high integration complexity	Energy down 36.3%, carbon down 40.8%, peak down 31.8% [117] (L1)

Table 9 defines the 1–5 anchor levels for each criterion, including the intermediate levels 2 and 4, which are assigned when the evidence satisfies the lower anchor fully and the higher anchor partially; for example, a latency of seconds to one-minute scores 4 on computational speed. Scores are not intrinsic properties of an algorithm family. They summarize the implementations, hardware, datasets, and network sizes reported in the cited TES and energy studies, and they are valid only for that evidence base. Table 10 therefore links every score to its supporting studies and codes each of the 78 cells as E (two or more supporting studies), S (a single study), or I (inferred from method properties because TES-specific evidence is insufficient). Of the 78 cells, 41 (52.6%) are coded E, 22 (28.2%) S, and 15 (19.2%) I; the 37 S and I cells are reported as provisional. Two authors

independently scored the matrix using the anchors; 66 of 78 cells (84.6%) agreed on first pass, with a quadratic-weighted Cohen's kappa of 0.81, and the remaining 12 cells were resolved through discussion with a third author. A sensitivity analysis perturbed all 37 provisional cells by -1 , 0 , or $+1$ with equal probability in 10,000 Monte Carlo draws. For every criterion, at least one of the baseline leading methods remained a leading method in 100% of draws. When all provisional cells were set to the neutral value of 3, the leaders for computational speed (RL), interpretability (MILP), data efficiency (MILP), and robustness (hybrid deep learning and digital twins) were unchanged, whereas the leaders for predictive accuracy and scalability narrowed to methods with E-coded evidence. Mean scores across criteria span only 3.0 to 3.5, so the framework does not support an overall ranking of methods, and none is offered. Scores were assigned by the authors from the quantified evidence; these scores represent a structured qualitative synthesis, not a meta-analysis. Figure 10 presents the resulting score matrix with the evidence codes.

Table 9. Assessment criteria and anchor levels used for the comparative scoring (authors' definition), including intermediate levels.

Criterion	Definition	Score 1 Anchor	Score 2 Anchor	Score 3 Anchor	Score 4 Anchor	Score 5 Anchor
Predictive accuracy	Agreement with measured TES/load variables	Not demonstrated in TES studies	Errors above 15% or accuracy shown only on synthetic data	Moderate errors (roughly 5–15%)	Errors of 3–5% or R^2 of 0.95–0.98 on measured data	$R^2 \geq 0.98$ or error ≤ 1 –3% in cited studies
Computational speed	Online decision or inference latency	Hours (offline only)	Tens of minutes to one hour	Minutes (near real-time)	Seconds to one minute	Milliseconds to seconds [57]
Interpretability	Traceability of decisions to causes	Black-box deep models [137]	Post hoc explanations only (feature attribution, saliency)	Partially traceable (kernels, trees, rules)	Explicit objective and constraints with learned sub-models	Explicit constraints and physics (e.g., MILP)
Data efficiency	Performance from limited data	Requires years of high-resolution data	Requires one year of data or large pre-training sets	Months of data or transfer learning	Weeks of data with a physical prior or calibrated model	Effective with weeks of data or expert priors
Scalability	Coordination of many distributed assets	Single-asset demonstrations only	Few assets within one building	Building cluster demonstrations	District network in simulation (hundreds of nodes)	District or city network demonstrations
Robustness	Performance under distribution shift	Degrades sharply off-distribution	Degradation reported without a recovery mechanism	Retraining restores performance	Online adaptation demonstrated in simulation	Validated adaptation or uncertainty handling

The matrix shows that no single method dominates all criteria. Transformer-based and hybrid deep models achieve the highest accuracy and scalability but the lowest interpretability and data efficiency; the Transformer scores are based on a single study [58]. MILP offers the strongest interpretability and optimality guarantees but limited robustness to nonlinearity and scale. RL scores highly on speed and adaptability after training, yet its sample inefficiency and opaque policies limit trust in safety-critical operation [42]. MPC occupies an intermediate position with balanced scores of 3 to 4 on all criteria, which explains its frequent use as the benchmark against which learning-based controllers are tested. Classical methods such as SVMs and evolutionary algorithms remain competitive

when data are scarce or when transparent design optimization is required. Vetter et al. [65] provide a rare like-for-like benchmark: deep RL approached the MILP optimum (8.78% versus 10.06% cost reduction) while requiring only 22% of the computation time, illustrating the accuracy-speed trade-off directly. Method selection should therefore follow application priorities: deep learning for accuracy-intensive forecasting, MILP for auditable scheduling, RL for fast adaptive control, and data-efficient methods in resource-constrained settings.

Table 10. Evidence supporting each score: supporting studies, number of studies, and evidence codes per criterion (A accuracy, S speed, I interpretability, D data efficiency, Sc scalability, R robustness; E two or more studies, S one study, I inferred).

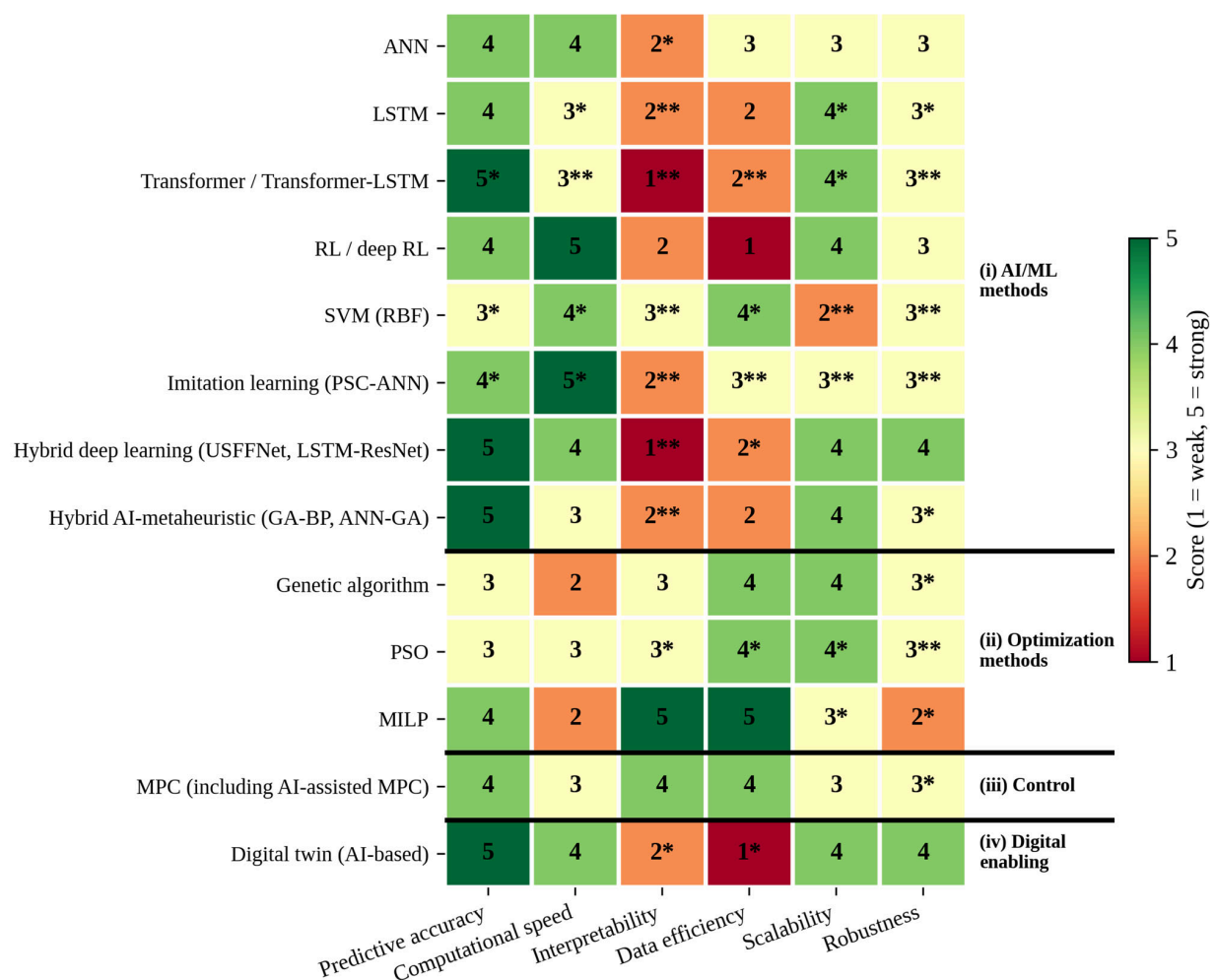
Method	Scores (A/S/I/D/Sc/R)	Supporting Studies	<i>n</i>	Evidence Codes (A/S/I/D/Sc/R)	Provisional Cells
ANN	4/4/2/3/3/3	[39,64,115,116,126]	5	E/E/S/E/E/E	1 of 6
LSTM	4/3/2/2/4/3	[58,106,112]	3	E/S/I/E/S/S	4 of 6
Transformer/ Transformer-LSTM	5/3/1/2/4/3	[58]	1	S/I/I/I/S/I	6 of 6
RL/deep RL	4/5/2/1/4/3	[44,57,60,65,95,138]	6	E/E/E/E/E/E	0 of 6
SVM (RBF)	3/4/3/4/2/3	[111]	1	S/S/I/S/I/I	6 of 6
Imitation learning (PSC-ANN)	4/5/2/3/3/3	[88]	1	S/S/I/I/I/I	6 of 6
Hybrid deep learning (USFFNet, LSTM-ResNet)	5/4/1/2/4/4	[112,134]	2	E/E/I/S/E/E	2 of 6
Hybrid AI-metaheuristic (GA-BP, ANN-GA)	5/3/2/2/4/3	[56,116,126,128]	4	E/E/I/E/E/S	2 of 6
Genetic algorithm	3/2/3/4/4/3	[56,91,116,132]	4	E/E/E/E/E/S	1 of 6
PSO	3/3/3/4/4/3	[35,67]	2	E/E/S/S/S/I	4 of 6
MILP	4/2/5/5/3/2	[65,66]	2	E/E/E/E/S/S	2 of 6
MPC (including AI-assisted MPC)	4/3/4/4/3/3	[44,68,108,139,140]	5	E/E/E/E/E/S	1 of 6
Digital twin (AI-based)	5/4/2/1/4/4	[40,115,117,141,142]	5	E/E/S/S/E/E	2 of 6

5.3. Benefits, Drawbacks, and Risks of AI-Based TES Operation

The documented benefits of AI in TES operation are substantial but bounded. Restricting the synthesis to category (a) studies, AI-based control and optimization deliver simulated energy savings of 8.2–64.3% ($n = 4$ studies with percentage outcomes), simulated peak load reductions of 35.5% [63] and load shifts of 74% [121], and emission reductions of 8.7–60% ($n = 2$). Field-validated or operational outcomes for intelligent TES control are limited to 17% energy savings in a real building [60] and a 28.5% share of demand from a monitored BTES system [62]. The wider 0.8–66% cost reduction ranges arise from studies in categories (b) and (c) and include savings from batteries, hydrogen, and appliance scheduling. IoT monitoring platforms enable real-time data acquisition, predictive maintenance, and adaptive control in smart buildings and district systems [33,34]. Digital twins integrate sensor data, simulation, and analytics to test operating scenarios before deployment [143,144], and digital twin-enabled systems have improved forecasting accuracy and operational efficiency by over 20% [142,145], again in simulation.

These benefits carry inherent drawbacks that the TES literature often understates. First, interpretability: high-performing deep models are black boxes, and post hoc explanations can be unreliable for high-stakes operational decisions [137]. Limited transparency reduces operator trust in safety-critical grid operations. Second, data and computing demands: deep and hybrid models require large volumes of high-quality sensor data and substantial training compute, which conflict with the data scarcity in newly built TES networks [146]. Third, distribution shift: models trained on historical data are susceptible to concept drift and non-stationary demand, so reported accuracies on historical datasets overstate field performance [42]. Fourth, the simulation-to-reality gap: 37 of 47 quantitative studies (78.7%)

are simulation-only, whereas real building RL deployments, such as Svetozarevic et al. [60], remain the exception. Fifth, cybersecurity: digital coordination widens the attack surface, with demonstrated peak load increases of 17.4% under simulated attacks and demand falsification of up to 21.5% [111,112]. Sixth, dependency and fallback: networks operated by learned policies require verified, rule-based fallbacks, since model failures or sensor losses can propagate across coupled districts. Adaptive predictive control studies also report inconsistent results across operating conditions [140], and the benefits of PCM control depend strongly on climate and design [147]. Consequently, claims that AI integration alone will secure urban decarbonization are not supported by current evidence; AI is an enabler whose net benefit depends on data quality, interpretability requirements, and cyber-resilient system design.



No mark: two or more supporting TES/energy studies (E); * single supporting study (S); ** inferred from method properties, TES-specific evidence insufficient (I).

Figure 10. Comparative scoring of thirteen AI and intelligent digital method families in four groups against the six criteria defined in Table 9 (scale 1 = weak to 5 = strong; scores assigned by the authors from the evidence in Table 10; asterisks mark provisional cells).

6. Applications, Impacts, and Case Studies

6.1. Applications Across Urban Infrastructure

Intelligent TES networks serve three principal application domains in UESs. The first is buildings, which account for roughly 37% of worldwide energy-related CO₂ emissions [105]. TES integrated with HVAC systems stores thermal energy during off-peak hours for use during peak periods, reducing electricity consumption and improving comfort [61,148].

On-site experiments with active TES air-conditioning under transactive control confirm the practicality of building-level demand response [61] (L3, a). The second domain is district energy, where TES integrated with district cooling networks manages load, reduces peak electricity demand, and improves reliability [102]. The third domain is industrial waste heat, which can be captured in concrete, nanofluid, or PCM-based stores and redistributed to nearby buildings or districts [149,150]. Applications span sectors with quantifiable outcomes. Renewable-assisted cold TES air-conditioning substantially reduces emissions, although intermittency persists [151]. Cold TES in residential cooling delivered electricity savings of up to 14.5% and cost reductions of 42.3% in Spain [118] (L1, T). Lifecycle-oriented retrofits combining thermal storage and smart technologies achieved a 73% reduction in global warming potential [152]. PCM stores also serve controlled-environment agriculture [153] and refrigerated warehouses, where compatibility and control remain the key challenges [154]. On the materials side, bio-based PCMs could address the building sector, which accounts for over 30% of energy consumption [53]; solar TES walls could improve building self-sufficiency [50]; and transparent wood PCM composites achieved 89 J/g of latent heat with a 39% lower environmental impact [79].

6.2. Impacts on Energy, Emissions, and Grid Operation

Deploying TES networks produces four documented impact categories. Peak load reduction decreases electricity demand during high-consumption periods and reduces grid strain, complementing industrial and residential demand response [155,156]. Renewable utilization improves through storage-enabled load balancing [157]; hybrid TES-battery configurations cut grid imports and renewable curtailment by up to 35–40% in Portuguese energy communities [158]. Reliability improves through AI- and IoT-enabled predictive maintenance and real-time monitoring [143], with digital twins supporting scenario testing and operational optimization [144,159,160]. Reported carbon reductions attributable to combined TES and intelligent management range from approximately 20% to 40% across the reviewed case studies [159,160]. These figures should be read with caution: they derive predominantly from simulations with favorable tariff and data assumptions, and few have been verified against long-term measured data. At the system-level, large-scale TES supports sector coupling and deep decarbonization of urban networks [114,161]. AI-driven management enhances grid flexibility and reduces peak demand [162], and combining TES with grid-enhancing technologies accelerates decarbonization while reducing infrastructure stress [87,163]. ML also supports component design: gradient boosting predicted thermo-physical properties of compressed-air storage with correlation coefficients above 0.999 [164], and IoT-enabled thermal modeling improved building demand estimation [165].

6.3. Case Studies of Intelligent TES and Smart Energy Systems

Table 11 compares recent intelligent TES and smart energy case studies across countries, objectives, methods, and impacts, with validation level and TES-centrality category added. The reported outcomes include collector efficiency gains of 0.9–1.2% with 9.5–15% higher coefficient of performance in Indian solar cooling [119], 55.4% thermal efficiency with 931 t/year CO₂ reduction in Chinese solar cogeneration with molten salt storage [128], 40–50% faster simulation execution in digital twin-controlled solar-hydrogen systems [141], 55% energy cost reduction in Norwegian smart renewable communities [126], leakage-free cold storage cycling with biomass brine gels [166], and 60.9% CO₂ reduction in a near-zero energy hotel system [116]. All seven cases are simulation-based (L1) except the brine-gel material study (L2), and only three [119,128,166] place TES at the centre of the system boundary.

Table 11. Case studies on TES and smart energy systems with validation level and TES-centrality category.

Reference	System	Country and Research	Objective	Methodology	Applications	Impacts	Future Scope	Level/Category
Lal et al. [119]	Intelligent solar-assisted lithium bromide absorption system	India (Solar cooling system)	Develop solar-assisted cooling/heating system using TES	Chimp-based Recurrent Model	Solar cooling, building thermal management	Collector efficiency increased 0.9–1.2%, COP improved ~9.5–15%	Scalable solar thermal cooling technologies for buildings	L1/a
Tian et al. [128]	Solar cogeneration with molten salt TES	China (Industrial oil terminal)	Reduce carbon emissions and energy consumption using TES	Aspen Plus simulation, ANN-NSGA-II optimization, thermodynamic modeling	Industrial energy systems, solar thermal power	Thermal efficiency 55.43%, IRR 11.23%, CO ₂ reduction 931.36 t/year	Real-time dynamic optimization based on electricity price and weather	L1/a
Goudarzi et al. [141]	Hybrid CSP-electrolysis thermal-hydraulic system	Sweden/EU	Develop real-time control framework for hybrid solar-hydrogen energy systems	GPU-accelerated solver, hierarchical control architecture, digital twin	Hydrogen production, district heating, solar power plants	Simulation execution reduced 40–50%, stable operation during 45% load ramps, hydrogen purity 0.82 mole fraction	AI-driven digital twins for large-scale HES	L1/b
Karkon et al. [126]	Smart renewable energy system with hydronic units	Norway	Develop smart integrated energy system using PVT, biomass, and heat pumps	TRNSYS-MATLAB simulation, Grey Wolf Optimization, AI-assisted optimization	Smart grids, hybrid renewable energy systems	Energy cost reduction 55%, emissions reduced to 36.3 g/kWh, annual clean energy generation 17,830 MW	Smart microgrid integration and renewable penetration optimization	L1/b
Wang et al. [166]	Biomass brine gels for TES	China	Develop environmentally friendly low-temperature TES materials	Biomass polymer networks, brine gels, graphite flakes, numerical simulations	Cold storage, biological temperature control	Improved thermal conductivity and mechanical strength; stable cold storage performance with leakage-free cycles	Smart cold chain storage and biomedical temperature regulation	L2/a
Vetter et al. [65]	RL Control for Energy Communities	Austria	Evaluate RL-based energy system control compared with MILP optimization	Deep Q-Network RL vs. MILP optimization	Residential energy communities with PV and TES	MILP reduced costs 10.06%, RL reduced cost by 8.78%, and computation time required only 22%	Real-time AI-based energy management for distributed energy systems	L1/b
Du et al. [116]	Solar-Assisted Hybrid Energy System for Hotel	China	Develop near-zero energy hybrid building system integrating solar and TES	EnergyPlus, TRNSYS simulation, ANN-GA optimization, Sobol sampling	Smart buildings, solar cooling/heating systems	CO ₂ emissions reduced 60.86%, operational cost \$1.78/hour, LPSP 0.42	Deployment of intelligent renewable systems in hospitality and commercial buildings	L1/b

Building-focused studies complement these system cases. PCM-integrated lightweight walls in German and USA climates enhanced thermal capacity, with orientation strongly influencing performance [167]. Reviews of building automation report that adaptive control and MPC improve energy management, although savings vary widely across operating conditions [168]. Fuzzy logic control of hybrid solar-gas-electric systems with PCM storage cut energy costs to 35% of the initial value with 12% monthly savings [169]. Hierarchical MPC integrating vehicle-to-building operation maintained comfort and reliability under forecast uncertainty [139], and physics-informed unsupervised learning for distributed energy resources cut computational complexity by 73% and carbon emissions by 46% [170]. Hybrid sorption TES with battery storage in PV greenhouses reduced annual energy dependency by 19.2% and battery cycling by nearly 30% [120] (L1, a). Dynamic-priority flexibility quantification for grid-interactive buildings achieved an average load shift of 74%, with active TES contributing 50.8% [121] (L1, a). Decentralized multi-agent RL across six-building neighborhoods exhibited 4–5% variation in grid purchases, with computational costs rising linearly with agent count [138]. In off-grid contexts, PV-driven vapor-compression reached 100% solar fraction in hot-arid climates, with TES reducing battery dependence [171].

Across the NZEB case studies compiled in Table 12, TES consistently improves building and urban energy flexibility, with simulated peak load reductions of 25–35% and significant carbon savings. Uncertainty-tolerant intelligent controls substantially enhance TES performance. Economic viability depends heavily on tariffs and sizing: green tariffs cut payback periods by 17–18%, and larger storage reduced payback by nearly 40% [122]. A major gap remains for tropical climates, since most validated studies come from temperate or dry regions, leaving high wet-bulb and monsoon conditions unverified. Only two of the ten NZEB cases, the monitored Vienna school [124] and the calibrated reduced-order model of the same building [59], exceed validation level L1, and both are heating-dominated.

Table 12. Case studies on TES for NZEBs (compiled by the authors from the cited sources) with validation level and TES-centrality category.

Reference	Level (Scale)	Focus	Key Findings	Further Research	Level/Category
Jin et al. [63]	Building	Physics-consistent neural network-enabled predictive control and bio-based PCM	44.3% cost saving; 35.5% peak load reduction; 5.31 °C indoor temp drop under extreme heat	District-scale PCM networks; tropical humidity/monsoon validation; bio-PCM lifecycle cost	L1/a
Alawadhi et al. [104]	Urban	WHR (data centre) + TES for district energy	TES analytical hierarchy process score 0.78, 30% GHG reduction	Pilot tropical district cooling with data centre waste heat; dynamic pricing policy	L1/b
Serageldin et al. [59]	Building (scalable)	Reduced-order building energy model for hybrid TES (district + geothermal + solar thermal)	Mean percentage error of 12.65% and a MAE of 14.03%	Tropical school districts; PCM + humidity; co-simulation with urban microclimate	L2/a
Mulani and Ling [122]	Building	NZEB optimization: PV + battery + air-conditioning and water-heating (TES via water-heating)	Green tariffs reduce payback 17–18%; larger battery (12.7–32.4%) cuts payback 39–41%	Air-conditioning and water-heating as TES in tropical high-density housing; occupant hot-water profiles	L1/b
Esmailzadeh et al. [123]	Building	Adaptive control for hybrid HVAC	90% comfort compliance	District TES with optimized fuzzy sliding mode controller under tropical uncertainty; ice/PCM storage for flexibility	L1/c

Table 12. Cont.

Reference	Level (Scale)	Focus	Key Findings	Further Research	Level/Category
Hainoun et al. [124]	Building + grid	NZEB school with geothermal heat pump, solar thermal, PV, district heating interaction	Self-supply 124% (56.6 MWh surplus); 20.6 kg CO ₂ /m ² saving	Tropical cooling-dominated replication; TES rejection under high wet-bulb; monsoon vs. dry seasons	L4/b
Ataya et al. [125]	Building-urban	ORC hybrid systems (solar thermal + biomass) for NZEB	Solar-ORC air-conditioning: 97% energy saving; biomass-solar ORC: 97.1% heat, 25.9% electricity	ORC + cold TES for tropical cooling; low-temp ORC with solar + PCM for evening peak	L1/b
Alotaibi [68]	Building	Chance-constrained MPC + hybrid forecast (hot-desert office)	Electricity –14.0%, peak –24.9%, HVAC –19.0%; comfort 96.7%	District chilled water/ice storage in tropical cities	L1/c
Valsan et al. [127]	Urban (microgrid cluster)	Spatiotemporal deep learning for virtual energy exchange (India)	Grid dependency –30.7% (19.1 to 13.2 MWh/yr); cost saving >INR 15,000	Virtual thermal energy exchange; tropical monsoon storage scheduling	L1/c
Firoozi et al. [172]	Urban	Green architecture synthesis (envelopes, controls, policy)	Lifecycle payback attractive under tariffs; co-benefits for health/comfort	Integrate intelligent TES into tropical building codes; latent vs. sensible storage for humid heat	Review

6.4. Roadmap Toward Net-Zero Energy Cities

Figure 11 illustrates a staged pathway to a net-zero city, synthesized by the authors from the reviewed literature. It begins with a baseline assessment of energy use, emissions, and cooling demand, followed by policy frameworks covering targets, building codes, and incentives. Core interventions include energy efficiency, renewable integration, TES, district energy systems, smart grids, and AI-based management, interconnected through hybrid storage and city-scale integration, enabling sector coupling between buildings and transport. The outcomes are reduced peak load, increased renewable share, and lower emissions. For tropical countries, national projections indicate sharply rising cooling demand [173], and TES deployment is expected to expand alongside district cooling infrastructure [174]. Whether integrated AI-driven thermal grids can deliver city-scale benefits by 2050 depends on resolving the validation, economic, and governance barriers detailed in Section 7; the projected benefits remain conditional on evidence that does not yet extend beyond district-scale.

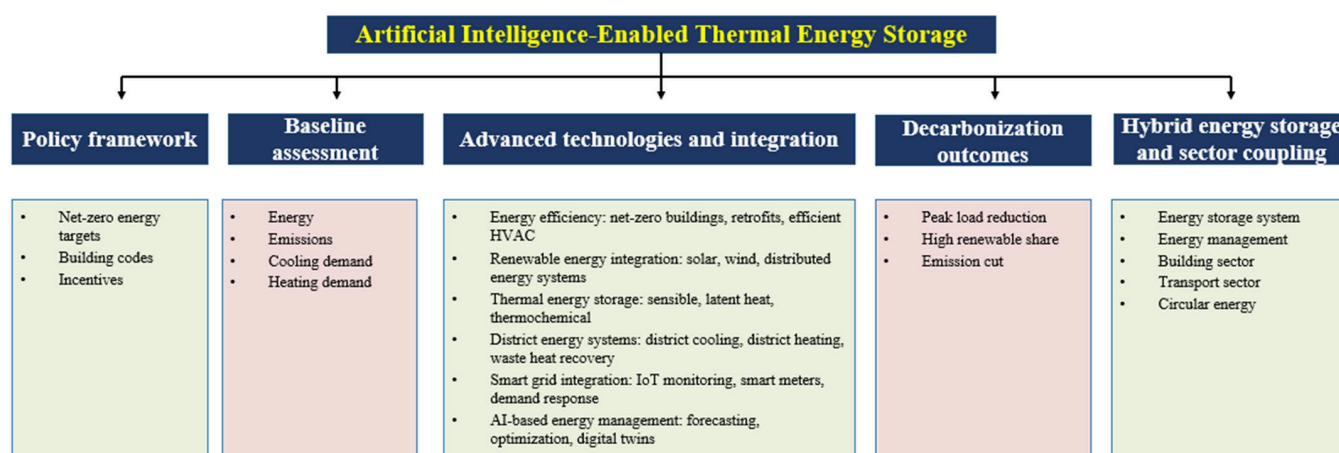


Figure 11. Roadmap to net-zero energy cities.

7. Limitations, Challenges, and Future Research Directions

7.1. Limitations of This Review and of the Field

This review is based on published literature and therefore cannot validate the intelligent TES network concept against new experimental or operational data. The evidence base is also structurally imbalanced: most reviewed studies address component-level innovations or building-scale implementations, and validated city-scale TES networks do not yet exist. Table 13 maps each limitation to the research direction that addresses it and to the minimum validation level required before the direction can be considered resolved. The following limitations and challenges constrain deployment.

Table 13. Mapping of identified limitations to research directions, required evidence, and target scale.

Limitation	Research Direction	Minimum Evidence Required	Target Scale	Related Sections
No validated multi-district intelligent TES network	Coordinated pilots of distributed TES assets across two or more districts with a shared objective	L3 field demonstration with at least one monitored cooling season	District to city	4.3, 4.4
Tropical district cooling with TES unverified	Monitored district cooling pilots under high wet-bulb and monsoon conditions	L3–L4 with measured COP, peak reduction, and water use	District	4.2, 6.3
Simulation-to-reality gap (78.7% of studies L1)	Benchmarking of AI controllers against MPC and MILP baselines on real buildings	L2 calibrated models followed by L3 campaigns	Building to cluster	5.2, 5.3
Heterogeneous baselines and metrics	Adoption of the normalized metrics of Section 2.3 and reporting of baseline, period, and tariff	Reporting standard applied in new studies	All	2.3, 4.4
Concept drift and interpretability	Online learning, uncertainty quantification, physics-informed and explainable models	L2 with deliberate distribution shift tests	Building to district	5.3, 7.2
Cyber vulnerability of coordinated storage	Anomaly detection, secure protocols, and verified rule-based fallbacks	L2 hardware-in-the-loop attack testing	District to city	4.3, 5.3
Thin techno-economic and financing evidence	Lifecycle cost, tariff sensitivity, and business models for developing economies	Measured cost data from L3–L4 projects	District to city	6.2, 7.2
Material durability and manufacturability	Cycle testing beyond 5000 cycles and lifecycle assessment of composite PCMs and thermochemical materials	L2 long-duration testing; L3 in building modules	Component to building	3.2, 3.3

- Scalability, interoperability, and long-term operational performance across diverse urban environments remain insufficiently explored, and pilot evidence beyond single districts is absent.

- Techno-economic evidence is thin for tropical cities; location-specific assessments of district cooling with TES under high wet-bulb conditions are largely missing.
- High initial investment, financing barriers, infrastructure readiness, and policy support are seldom analyzed, limiting real-world applicability of reported findings.
- Long-term stability, environmental impact, and large-scale manufacturability of advanced materials such as nano-enhanced PCMs remain uncertain.
- AI models with high accuracy on historical datasets are susceptible to concept drift and non-stationary demand, and their black-box nature limits operator trust in safety-critical operation.
- Dependence on large volumes of high-quality data, high computational requirements, cybersecurity risks, and heterogeneous digital platforms further constrain large-scale integration.
- The evidence-quality and scoring frameworks introduced here are qualitative. Validation levels were assigned based on published descriptions; inter-rater agreement was measured only for a two-author panel; and the scores rest on 32 supporting studies, with 37 of 78 cells being provisional.

7.2. Future Research Directions

Future work should prioritize large-scale pilots and real-world demonstrations of intelligent TES networks, particularly district cooling with TES in tropical cities, to convert simulated benefits into measured evidence. Specific directions follow.

- Develop integrated urban energy models that couple TES, renewable generation, and smart grid infrastructure, and validate them against measured district data.
- Conduct techno-economic analyses of lifecycle costs, return on investment, and financing mechanisms tailored to developing economies and tropical climates.
- Establish regulatory frameworks, financial incentives, and standardized guidelines that enable municipal-scale TES procurement and operation.
- Advance high-performance, cost-effective, and environmentally sustainable TES materials, supported by lifecycle assessments of recyclability and long-term stability.
- Explore hybrid systems that combine TES with renewable sources, battery storage, and WHR, since TES alone cannot meet large-scale urban thermal demand.
- Develop hybrid AI architectures that embed power system physics, together with federated learning, digital twins, and explainable AI, to improve scalability, transparency, and trust.
- Improve robustness against concept drift through online learning, uncertainty quantification, and real-time model adaptation, and benchmark AI controllers against interpretable baselines such as MPC and MILP.
- Strengthen cybersecurity frameworks and standardized communication protocols for secure integration of TES networks with smart grid infrastructure.
- Report validation level, TES-centrality, baseline, evaluation period, and tariff assumptions in every new TES-AI study so that future syntheses can pool results quantitatively.

Interdisciplinary collaboration across academia, industry, and government will be needed to translate these directions into scalable deployments for net-zero energy cities.

8. Conclusions

The transition toward net-zero cities requires transformation of UESs, particularly in rapidly urbanizing tropical regions where cooling demand is rising sharply. This review examined TES as an enabling technology for balancing supply and demand across building, district, and urban scales, and critically assessed the role of AI in TES operation. The major conclusions are as follows.

- Sensible, latent, and thermochemical TES offer complementary capabilities, with energy densities of 10–50, 50–150, and 150–500 kWh/m³, respectively, suited to deployment scales from single buildings to seasonal district storage.
- District-scale TES is commercially proven: over 2800 aquifer storage systems deliver more than 2.5 TWh of heating and cooling annually with 40–70% energy savings, and pit stores exceed 200,000 m³. In contrast, validated city-scale intelligent TES networks have not yet been reported; no study coordinates TES assets across two or more districts beyond simulation.
- AI methods improve TES operation measurably in simulation. Direct TES-AI studies report energy savings of 8.2–64.3%, peak reductions of 35.5%, and emission reductions of 8.7–60%, whereas field-validated intelligent control reports 17% energy savings in a single real building. Of 47 quantitative studies, 78.7% are simulation-only, and 8.5% are operational. The six-criteria assessment shows no dominant method; selection involves explicit trade-offs among accuracy, speed, interpretability, data efficiency, scalability, and robustness, and 47.4% of the scores remain provisional pending TES-specific evidence.
- The drawbacks of AI-based operation are material: limited interpretability, high data and computing demands, concept drift, and cyber vulnerabilities that raised peak load by 17.4% in a simulated attack. Deployment requires interpretable baselines, verified fallbacks, and cyber-resilient design.
- The critical evidence gap is tropical district cooling with TES. Most validated studies come from temperate or dry climates, whereas growth in cooling demand is concentrated in humid tropical cities; only two of the seven tropical studies achieve simulation-level validation.

This review has limitations that bound its conclusions. It synthesizes published evidence and could not generate new measurements. The search covered three databases and English-language documents, so non-indexed pilot reports and grey literature from utilities may be under-represented. The validation levels, centrality categories, and scores were assigned by a small author panel and, although inter-rater agreement was high, they remain qualitative judgments. The bibliometric analysis uses the lead author's country as a proxy for study location. Future work should extend the approach in three ways: by repeating the classification as new L3-L4 studies appear and pooling normalized outcomes in a formal meta-analysis once at least ten field-validated TES-AI studies exist; by adding databases and languages that capture Asian and Latin American deployment reports; and by applying the evidence-quality framework prospectively as a reporting checklist for new TES-AI studies. Expanding TES from individual buildings to district and city scales, supported by measured pilot evidence, transparent AI, and enabling policy, offers a credible pathway to reduce peak cooling demand and emissions in urban energy transitions aligned with Sustainable Development Goals 7, 11 and 13.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ATES	Aquifer thermal energy storage
ANN	Artificial neural networks
BTES	Borehole thermal energy storage
DHC	District heating and cooling
EV	Electric vehicle
GA	Genetic Algorithm
HES	Hybrid energy systems
HVAC	Heating, ventilation, and air-conditioning
IoT	Internet of Things
L1-L4	Validation levels (simulation, laboratory/calibrated, pilot/field, operational)
LSTM	Long Short-Term Memory
MAE	Mean absolute error
MILP	Mixed integer linear programming
ML	Machine learning
MPC	Model predictive control
NZEB	Net-zero energy buildings
ORC	Organic Rankine cycle
PCM	Phase change materials
PSO	Particle swarm optimization
PTES	Pit thermal energy storage
PV	Photovoltaic
RES	Renewable energy sources
RL	Reinforcement learning
SVM	Support vector machine
TES	Thermal energy storage
TRL	Technology readiness level
UES	Urban energy systems
WHR	Waste heat recovery

Nomenclature

A	Surface area (m^2)
C	Concentration of reactant (mol/m^3 or kg/m^3)
C_p	Specific heat capacity ($\text{kJ}/\text{kg}\cdot\text{K}$ or $\text{J}/\text{kg}\cdot\text{K}$)
H	Enthalpy (J/kg)
k	Thermal conductivity ($\text{W}/\text{m}\cdot\text{K}$)
k_r	Reaction rate constant (s^{-1})
L	Latent heat of phase change (kJ/kg)
m	Mass (kg)
Q	Heat stored or transferred (J or kJ)
T	Temperature (K or $^{\circ}\text{C}$)
t	Time (s)
α	Reacted fraction (–)
E_a	Activation energy (J/mol)
e_v	Volumetric energy density (kWh/m^3)

f_l	Liquid fraction (–)
I_0	Initial investment (currency)
N	Prediction horizon (steps)
$P_{\max}$	Peak electric load (kW)
R	Universal gas constant (J/mol·K)
u_k, x_k	Control and state vectors at step k
γ	Discount factor (–)
η_{rt}	Round-trip efficiency (%)
π	Control policy
Greek Symbols	
ΔH	Reaction enthalpy (kJ/kg or J/mol)
ΔT	Temperature difference (K or °C)
ρ	Density (kg/m ³)
$\nabla^2 T$	Laplacian of temperature (K/m ²)
∂	Partial derivative operator

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