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A comprehensive review and framework on the applications of digital twins for energy transition at the district level

Amin Jalilzadeh [a,*], Azarakhsh Rafiee [a], Peter van Oosterom [a], Thaleia Konstantinou [b]

[a] Section GIS Technology, Department of Architectural Engineering + Technology, Faculty of Architecture and the Built Environment, TU Delft, Julianalaan 134, Delft, 2628 BL, Netherlands

[b] Department of Architectural Engineering + Technology, Faculty of Architecture and the Built Environment, TU Delft, Julianalaan 134, Delft, 2628 BL, Netherlands

HIGHLIGHTS

- Building and grid digital twins operate in isolation despite critical interdependencies.
- Digital twins evolve from monitoring to autonomous district energy management.
- Proposed framework bridges semantic, temporal, and sequential planning gaps through integration.
- Framework transforms reactive grid expansion into proactive building-grid co-evolution.

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ABSTRACT

Districts face dual pressures: reducing carbon emissions while managing surging electricity demand from electrification and urban growth. Traditional grid expansion cannot match the speed and complexity required for modern energy transitions. District energy transitions require connecting different scales, from individual buildings to grid networks, and different timeframes, from daily operations to long-term planning. Despite growing interest in Digital Twin (DT) for energy management, their application to integrated district-level energy transitions remains poorly understood. This review investigates how DTs can enable district energy transitions by examining their applications in built environment and energy infrastructure at district level, analyzing implementations across Positive Energy Districts (PEDs), microgrids (MGs), and related district energy paradigms. DT components (physical models, core capabilities, data infrastructure, and functional evolution) are investigated to assess their integrative potential. The analysis reveals three disconnects: building and grid systems are modeled separately despite inherent interdependencies; operational insights rarely inform infrastructure planning; and intervention strategies overlook sequential dependencies. To address these gaps, we propose an integrated framework advancing DTs toward district energy planning. The framework bridges semantic, temporal, and sequential planning through: knowledge graph architectures enabling cross-domain data integration, coupled simulation pipelines capturing building-grid interactions, and reinforcement learning optimizing intervention sequences. Unlike optimization that fixes strategies upfront, sequential planning accommodates technology emergence and regulatory shifts inherent to multi-decade transitions. This integrated approach transforms DTs from domain-specific monitoring tools into strategic planning platforms where coordinated building improvements and distributed energy resources defer costly grid expansions while accelerating district decarbonization.

1. Introduction

1.1. The energy transition imperative

The global energy sector is undergoing a fundamental transformation towards sustainability, driven by urgent climate imperatives and international decarbonization commitments. This shift is characterized by three key trends: Decarbonization, Digitalization, and Decentralization (DDD) [1–3]. With cities consuming 75% of global energy and generating 70% of emissions [4], international targets—55% EU emission cuts by 2030 and increased renewable energy share toward

* Corresponding author.
Email addresses: A.jalilzadeh@tudelft.nl (A. Jalilzadeh), A.Rafiee@tudelft.nl (A. Rafiee), P.J.M.vanOosterom@tudelft.nl (P. van Oosterom), T.Konstantinou@tudelft.nl (T. Konstantinou).

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Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
BIM	Building Information Modelling
CIM	Common Information Model
CityGML	City Geography Markup Language
DDD	Decarbonization, Digitalization, and Decentralization
DERs	Distributed Energy Resources
DT	Digital Twin
EVs	Electric Vehicles
GIS	Geospatial Information Systems
HVAC	Heating, Ventilation, and Air Conditioning
IFC	Industry Foundation Classes
IoT	Internet of Things
KPIs	Key Performance Indicators
MGs	Microgrids
ML	Machine Learning
nZED	Near Zero Energy Districts
OGC	Open Geospatial Consortium
PEDs	Positive Energy Districts
PV	Photovoltaic
RESs	Renewable Energy Sources
RL	Reinforcement Learning
SCADA	Supervisory Control and Data Acquisition
UML	Unified Modeling Language

2050 [5,6]—demand urgent district-scale action. Decarbonization focuses on increasing adoption of Renewable Energy Sources (RESs) alongside technologies such as distributed generation, Electric Vehicles (EVs), and energy storage [2,7]. This transformation includes grid decentralization to enhance resilience, requiring coordinated solutions at district, urban, and building levels [8–11].

1.2. Districts as the critical scale

Districts represent a critical scale for energy transformation—large enough to achieve meaningful impact yet small enough to enable coordinated action among stakeholders. At this scale, the interactions between individual buildings, shared infrastructure, and local energy resources create both complexity and opportunity for optimization [12].

1.3. The challenge: coordinating district energy planning

Managing growing energy demand presents major challenges at the district scale, where both building operations and grid infrastructure must evolve to support decarbonization. Traditional grid expansion through transformers, cables, and substations remains costly and time-intensive. Meanwhile, building energy management has advanced significantly with sophisticated monitoring and control technologies. The complex interplay between building energy systems and grid infrastructure calls for new approaches that can support coordinated planning across different time horizons—from real-time operations to long-term strategic investments [13–18].

Various district-level energy transition concepts have emerged as strategies for achieving sustainability and decarbonization goals at intermediate scales between individual buildings and city-wide systems [19–22,47]. These approaches face challenges including renewable energy integration and grid stability due to variable generation [23]. Addressing these coordination challenges requires platforms capable of bridging building operations, grid infrastructure, and strategic planning—precisely the integration capabilities that Digital Twin (DT) technologies promise.

1.4. Digital twins as potential integrative platform

Digitalization, a pillar of the DDD movement, supports the establishment of sustainable districts by enabling the collection and analysis of extensive data sets. This, in turn, facilitates real-time monitoring, predictive analytics, and scenario planning [24]. Among emerging digital technologies, DTs represent a paradigm shift from static modeling to dynamic, data-driven representations that evolve with their physical counterparts. Exploring how DT technologies can support district-level energy transitions calls for systematic investigation of their applications across energy system components and coordination requirements [25,26,76].

Recent scholarly efforts have examined DTs in energy contexts from distinct disciplinary perspectives. Building-focused reviews [20,27] identified four application clusters—design optimization, occupant comfort, operation/maintenance, and energy consumption simulation—with Building Information Modelling (BIM)-Revit-Internet of Things (IoT) integration dominating but limited multi-building coordination. Grid-focused reviews [28,29] documented sophisticated Supervisory Control and Data Acquisition (SCADA)-enhanced simulation and power flow analysis capabilities, yet consistently treated buildings as aggregated load nodes rather than examining building-grid interactions. Urban reviews [30–32] attempted broader integration: taxonomies tracking BIM-to-DT evolution found most implementations concentrated in mid-level autonomy (BIM-IoT integration), while lifecycle analyses revealed energy applications remained isolated within single phases rather than spanning design through operations.

What remains unaddressed is systematic examination of how domain-specific DT capabilities could enable coordination across building and grid systems, how operational insights could inform strategic infrastructure planning, and how intervention strategies could account for sequential dependencies where building retrofits reshape grid requirements. This gap—between domain-specific sophistication and cross-domain coordination—motivates the present review's focus on district-level energy transitions where buildings and grids must co-evolve rather than optimize independently.

1.5. Research objectives and contribution

Addressing the integration gap identified above, this study advances understanding of DT applications for district energy transitions. While existing reviews examine DTs within specific domains—such as building performance or grid operations—separately, few systematically investigate coordination opportunities or propose frameworks to enable cross-domain planning. This review addresses this gap through three interconnected objectives:

1. Analyze DT implementations across district energy domains to identify patterns in current applications and integration approaches.
2. Synthesize technical requirements from emerging solutions: knowledge graphs, coupled simulation, and sequential optimization.
3. Propose an integrated framework to enable coordinated district energy planning across organizational and technical boundaries.

The proposed framework provides both conceptual architecture and technical guidance, structured around five integrated components—from physical infrastructure through data systems to stakeholder interfaces. Rather than requiring wholesale replacement of existing domain-specific tools, the framework identifies integration mechanisms that enable specialized capabilities to inform cross-domain planning.

Unlike prior domain-specific reviews, this study examines DT applications across multiple district energy concepts to reveal insights not visible within single-domain analyses.

1.6. Paper organization

The remainder of this paper is structured as follows. Section 2 establishes conceptual foundations for DTs and district energy transitions, providing context for the analysis that follows. Section 3 describes the systematic review methodology employed to identify and analyze relevant literature. Section 4 presents network analysis revealing structural patterns in the research landscape. Section 5 provides detailed examination of DT components, technologies, and applications across building and grid domains, documenting current capabilities. Section 6 synthesizes these findings into an integrated framework addressing identified coordination gaps. Section 7 discusses implementation challenges, research limitations, and implications for practitioners and researchers. Section 8 concludes by summarizing key contributions and future research directions.

2. Background

2.1. Digital twin fundamentals

DT concepts have evolved across multiple domains, resulting in varying definitions that reflect different application contexts and priorities. Grieves established the foundational DT concept as a comprehensive virtual model integrating physical system characteristics, real-time sensor data, historical data, and future prediction capability [26,33]. In energy management contexts, DTs integrate advanced modeling with data analytics, offering capabilities including real-time monitoring, simulation, scenario planning, and optimization [2]. Different research communities emphasize distinct aspects: high-fidelity virtual representations with bidirectional data exchange enabling monitoring and prediction [29], virtual models supporting simulation and decision support across building and grid systems [20], and multi-physics simulation approaches combining physics-based models with sensor data [2]. These definitions share core elements: virtual models of physical systems, bidirectional data flows, and capabilities spanning monitoring to predictive analysis.

For district energy applications, this study adopts a synthesized working definition: *DTs are dynamic virtual representations of physical energy systems that maintain bidirectional data exchange, enabling real-time monitoring, predictive simulation, and scenario evaluation to support decision-making across organizational and technical boundaries.* This definition encompasses both operational monitoring capabilities and strategic planning applications essential for district energy transitions. Having established what DTs are, we now examine the district energy planning contexts they must support.

2.2. District energy transition: planning contexts

District energy transitions involve coordinating multiple technologies and interventions across different spatial and temporal scales [2,7,13,14]. Various conceptual frameworks have emerged for district-level energy transitions, each emphasizing different aspects of sustainability, reliability, and energy balance [19–21,29].

Planning at the district scale spans temporal horizons from operational management to strategic infrastructure investment, and involves diverse stakeholders with distinct objectives and decision contexts [10,12,13,16]. Strategic horizons spanning 20–40 years face irreducible uncertainty—building stock turnover, climate impacts, policy evolution—rendering optimization's fixed-objective paradigm inadequate. Sequential frameworks treat planning as continuous adaptation rather than one-time solution.

Understanding how DT technologies are being applied across these district-level energy transition concepts motivates the systematic review described in the following section.

3. Article review methodology

3.1. Research design

This systematic review examines how DTs are being applied to support district-level energy transitions.

The investigation is guided by the following question:

1. How are digital twin technologies being applied across different scales and timeframes to support district-level energy transitions, and what framework can synthesize these applications to guide future implementations?

The review adopts an exploratory approach, examining DT applications across district-level energy transition concepts. This scope enables understanding how DTs function within different contexts and identifying opportunities for coordinated approaches (Fig. 1).

3.2. Search strategy

Systematic literature searches were conducted in Web of Science and Scopus on January 15, 2024, covering publications from 2015 through 2023. The search strategy combined DT terminology with energy management and district-level terms, as detailed in Fig. 2. Complete Boolean search strings combined core terms (“digital twin” OR “Virtual Model” OR “Cyber-Physical Model” OR “Digital Simulation”) with energy management terms (energy AND [manage* OR Communit* OR decentralized OR balance* OR microgrid]) and district-level terms (Positive OR zero OR Neutral AND Energy AND [District OR Block OR Neighbour OR Building]). Searches were limited to peer-reviewed publications in English without geographic restrictions. Fig. 2 illustrates the complete search and selection process following PRISMA guidelines.

3.3. Screening and selection

Following PRISMA guidelines, articles underwent multi-stage screening. Title screening assessed DT-energy relevance (N = 283 retained). Abstract screening evaluated district-scale focus, DT implementation, and energy management applications (N = 168 retained). Full-text screening required explicit DT frameworks, district-level system focus, energy transition relevance, and sufficient technical detail (N = 85 retained). An April 2025 update included recent 2024–2025 publications (Fig. 2). Articles were included if they: (1) addressed energy transition concepts or energy management in buildings, grids, or districts; (2) presented DT development, implementation, or applications for energy systems; and (3) provided sufficient technical detail on DT architecture or functionality at district scale. Forward and backward citation searching of key articles, combined with an April 2025 update search for recent publications, identified approximately 54 additional studies, yielding a final corpus of 139 articles for systematic review. Including methodological references and supporting literature, the complete bibliography comprises 139 references.

3.4. Analysis framework

Systematic analysis was performed using Atlas.ti software [34]. The analysis framework evolved through iterative coding, beginning with preliminary themes based on the research question and refining categories as patterns emerged from the literature. Complementing qualitative analysis, bibliometric network examination of keyword co-occurrence patterns and terminology revealed thematic clusters and research community structures within the corpus.

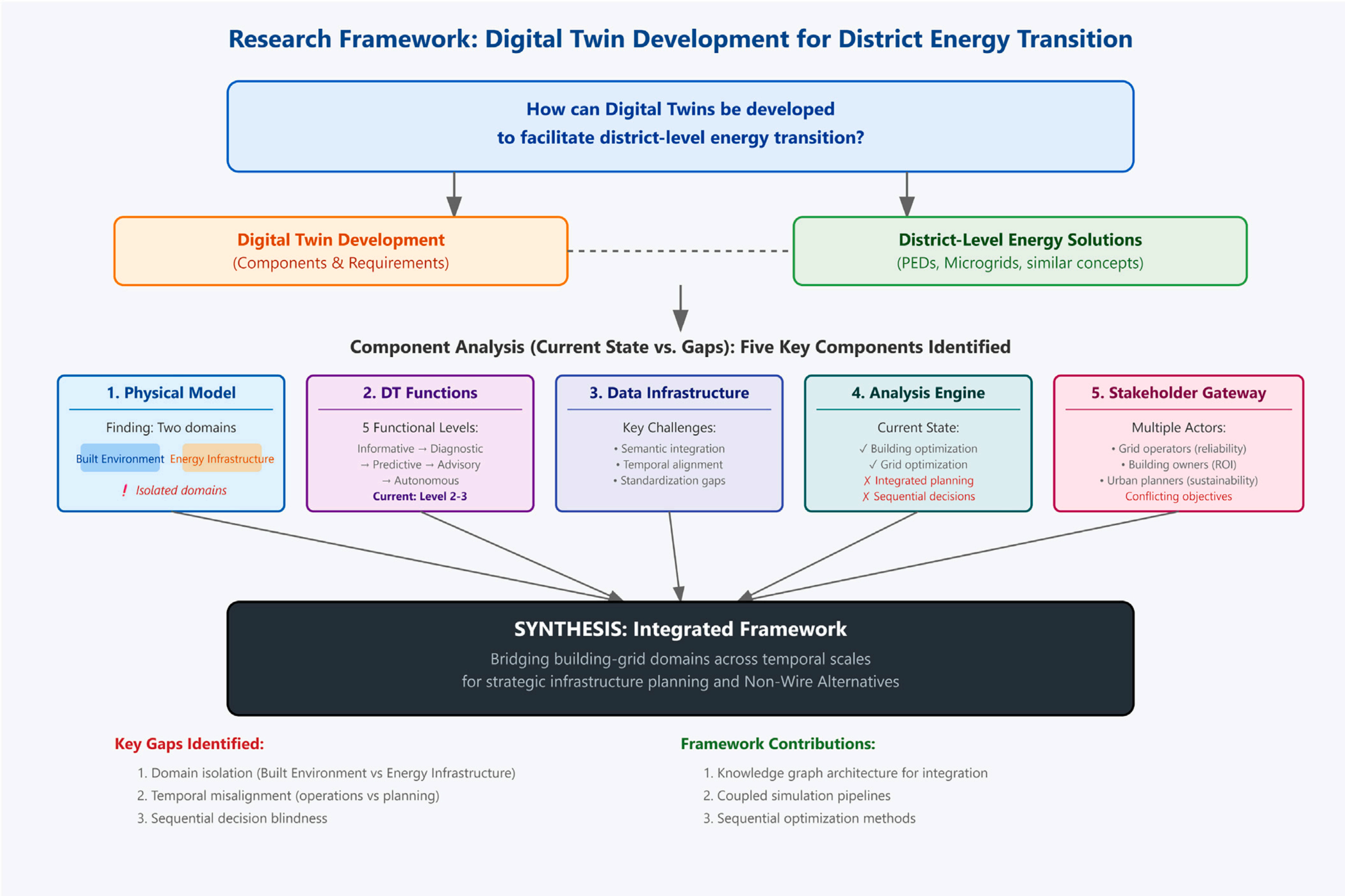


Fig. 1. Research framework overview.

Given the heterogeneous nature of included studies (simulation studies, framework proposals, case implementations, tool demonstrations) and the review's focus on synthesizing technical approaches rather than evaluating intervention effectiveness, quality considerations were embedded in inclusion criteria requiring peer-reviewed publications with explicit DT frameworks, district-level focus, and sufficient technical detail.

4. Bibliometric network analysis

4.1. Community detection in keyword co-occurrence networks

4.1.1. Network construction and community detection

Two complementary keyword co-occurrence networks were constructed following established bibliometric methodologies [35,36]: one from titles and abstracts using Term Frequency-Inverse Document Frequency vectorization to capture comprehensive semantic content, and another from author-assigned keywords to validate thematic structure [37]. Keywords were normalized using a thesaurus approach to consolidate variants (e.g., “optimisation” → “optimization”, “smart grids” → “smart grid”).

Community detection employed the Leiden algorithm [38] with RBConfigurationVertexPartition. Resolution parameter selection (γ = 0.5–2.0) optimized modularity [39], community count (4–10), and size distribution balance (largest community <30%) (Fig. 3). For abstracts, γ = 1.0 yielded optimal results (10 communities, Q = 0.5134, largest = 15.0%); for keywords, γ = 1.1 proved optimal (5 communities, Q = 0.5533, largest = 32.8%). Stability validation using Adjusted Mutual Information [40] confirmed AMI > 0.7 across γ = 0.8–1.2, indicating robust thematic structure.

4.1.2. Identified research communities

Keyword-level analysis identified five broad thematic clusters: (1) Digital Twin Technology & Smart Systems, (2) Smart Grid & Renewable Energy Systems, (3) Building & Community Energy Management, (4) Positive Energy Districts, and (5) Information Modeling & Interoperability. Abstract-level analysis revealed ten more granular communities: Distributed Energy & Digitalization, Artificial Intelligence (AI)/Machine Learning (ML)-Driven Renewable Optimization, Microgrid & Power Systems, Digital Twins & Semantic Integration, Building Energy Performance, Urban Energy Modeling & Geospatial Information Systems (GIS), Positive Energy Districts, District Monitoring & Control, Climate Impact & Emissions, and Knowledge Graphs & Planning. Community labels were assigned by the authors based on the dominant themes and keywords within each cluster.

The two analysis levels reveal consistent patterns with internal differentiation (Figs. 4 and 5). Broad keyword clusters fragment into more specialized abstract-level communities, revealing how major research directions contain distinct sub-specializations in modeling approaches, operational implementation, and strategic planning.

4.1.3. Community connectivity patterns

Network analysis revealed limited connectivity between communities. While some communities showed high internal cohesion (e.g., Positive Energy Districts: 0.667), external connections remained sparse, with most communities connecting to few keywords in other domains. Shared keywords primarily involved generic terms rather than domain-specific technical vocabulary, suggesting limited cross-domain integration in current research.

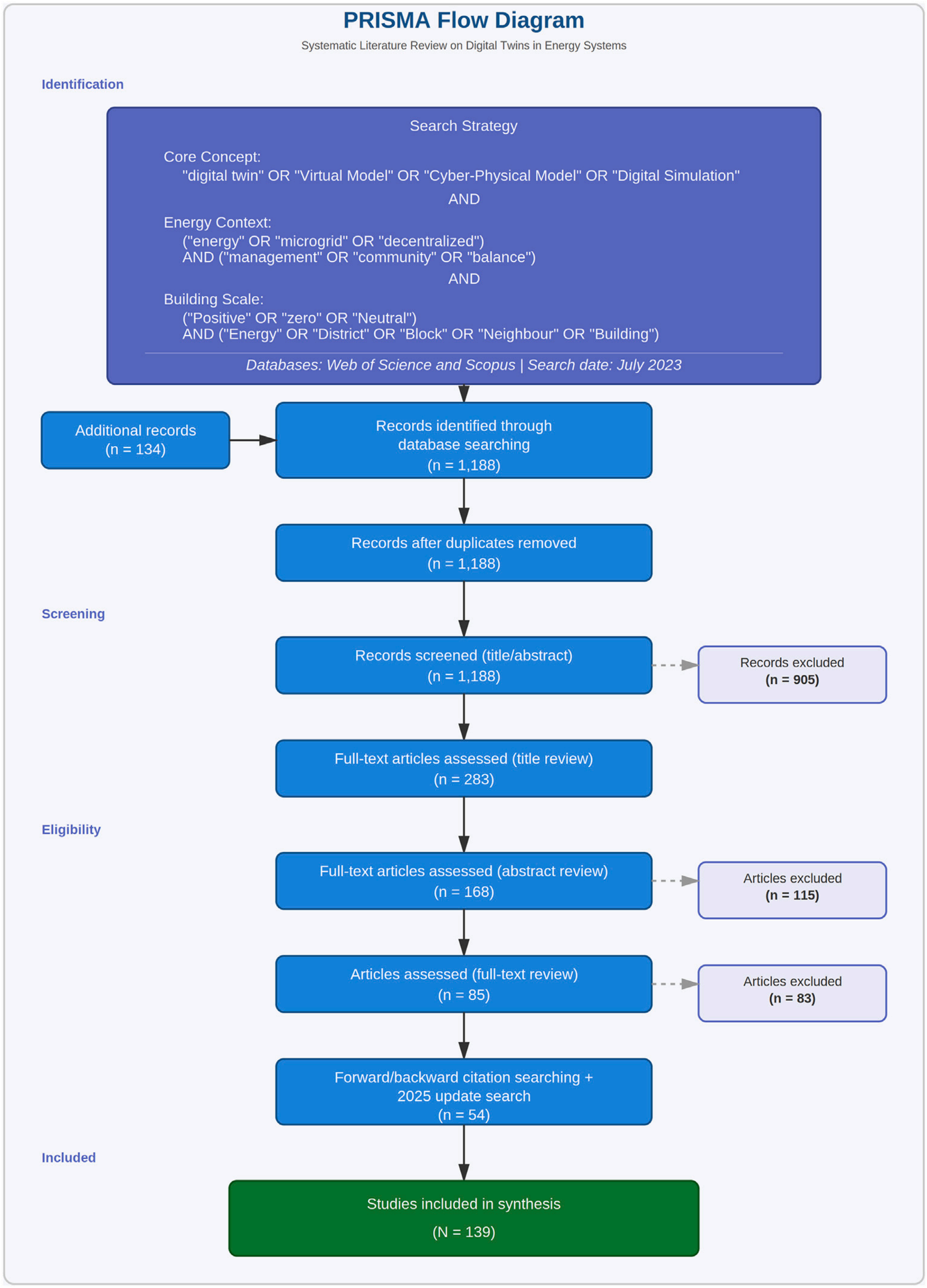


Fig. 2. The flowchart shows the search and inclusion strategy used in the literature review.

4.1.4. *Hierarchical clustering analysis*

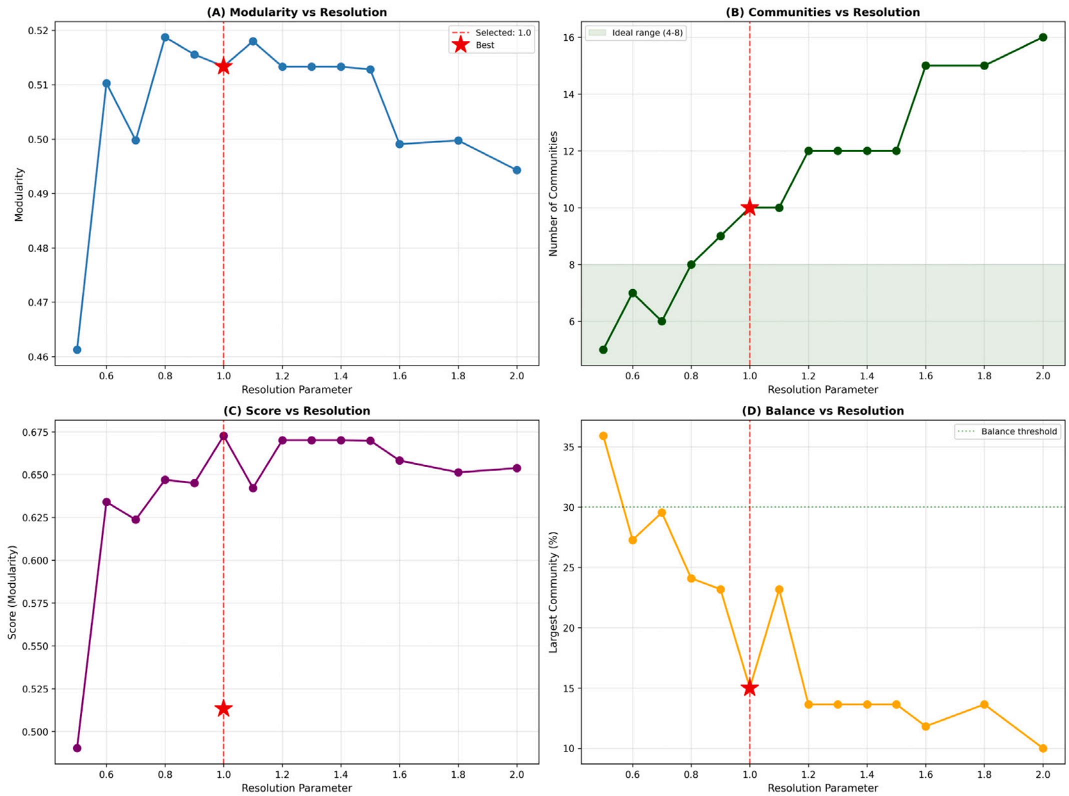
Hierarchical clustering revealed three meta-groups (Fig. 6) [41]. Communities were grouped by shared focus: physical infrastructure and spatial planning, building-district implementation, and operational control with algorithmic optimization. Meta-groups exhibited weak inter-cluster connections, indicating limited integration across these broader research orientations.

4.1.5. *Discoveries: three fundamental patterns*

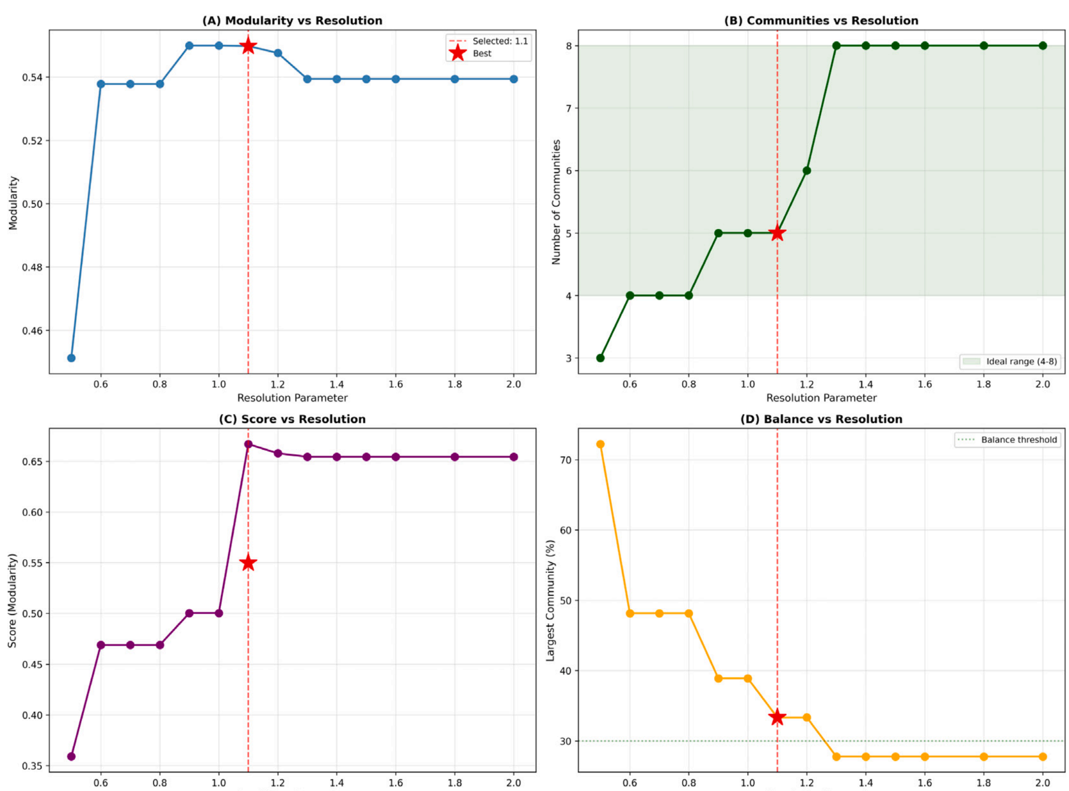
Network analysis revealed three patterns that illuminate the current state of DT research across district energy domains.

The digital twin paradox. Despite frequent reference across the network, “digital twin” appears within a community exhibiting low internal coherence, connecting primarily through generic terms (“data,” “model,” “system”) rather than domain-specific vocabulary. The term carries different meanings across domains: BIM-enhanced visualization (buildings), SCADA-enhanced simulation (grids), and data platform architecture (integration), reflecting different domain priorities.

Technology abstraction without integration architecture. Semantic technologies—knowledge graphs, ontologies, and information modeling—show high internal coherence but limited connections to building and grid application domains. Similarly, the Knowledge Graphs & Planning community maintains minimal engagement with



(a) Abstract-based network



(b) Keyword-based network

Fig. 3. Resolution parameter optimization for community detection. Optimal resolution marked with red star.

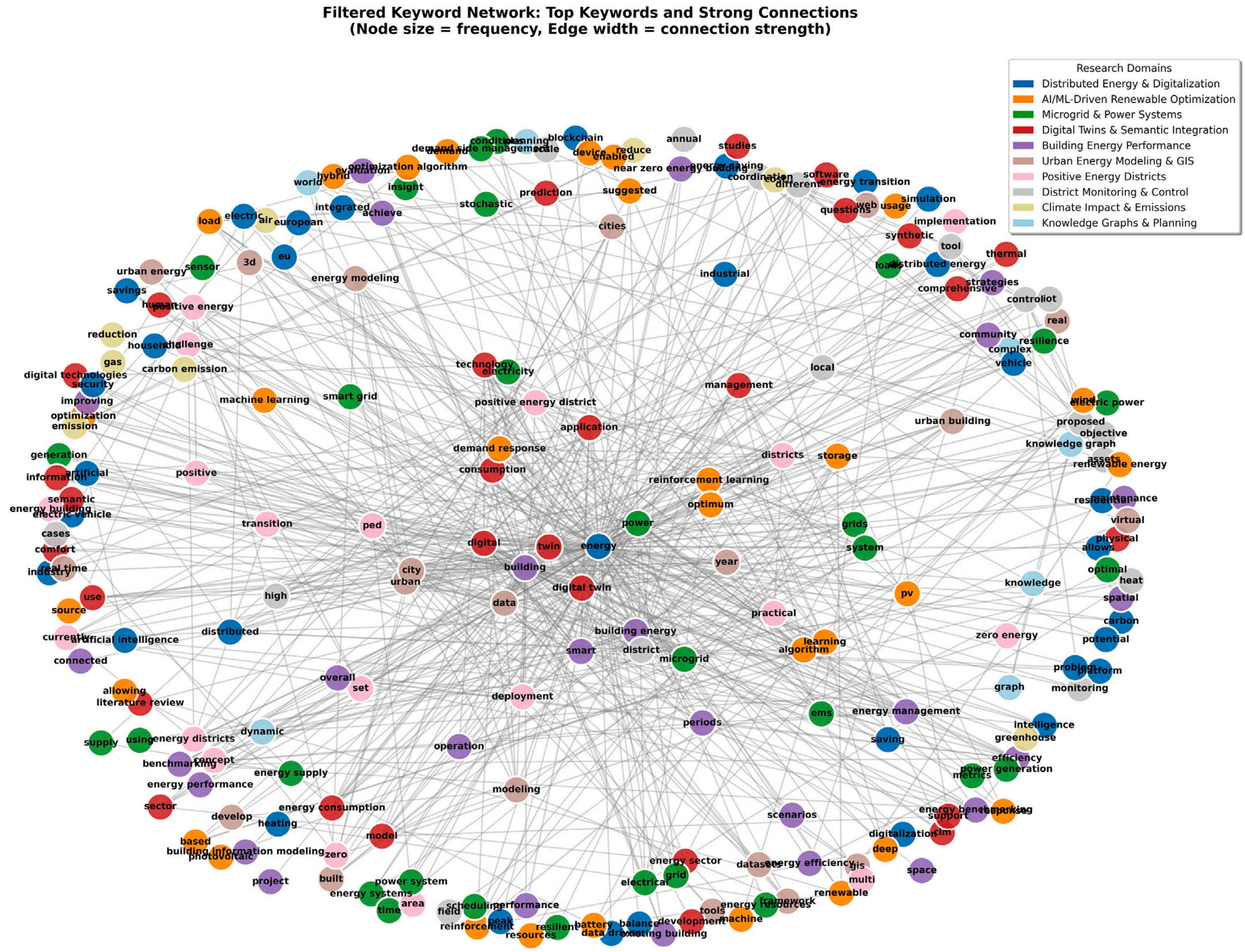


Fig. 4. Combined keyword co-occurrence network showing all identified communities. Node size represents keyword frequency, edge width indicates co-occurrence strength between keywords. Network filtered to include only edges with weight ≥2 for clarity.

operational implementation communities despite their theoretical capability to bridge heterogeneous data sources. This pattern suggests that these technologies have developed as research domains without yet achieving widespread deployment in district energy applications.

Goal-oriented and method-oriented research in parallel. Two patterns reveal systematic separation between outcome-focused and technique-focused research. The Positive Energy Districts community shows exceptional internal cohesion with rich outcome vocabulary but limited connections to technical implementation communities. Conversely, the Microgrid & Power Systems community focuses on technical capabilities (scheduling, resilience, control, power flow) with minimal engagement with sustainability outcomes or district-scale goals. The Climate Impact & Emissions community, though addressing environmental justification for district energy transitions, maintains separation from technical implementation communities.

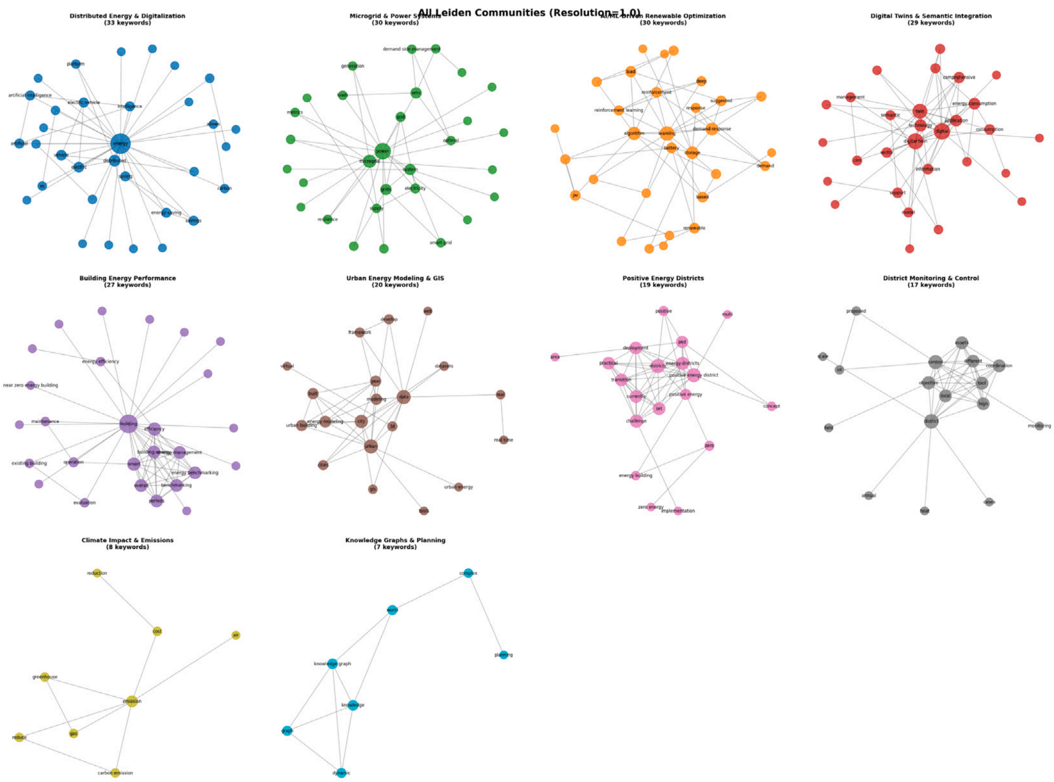
4.1.6. Interpretation: understanding the barriers

These structural patterns admit multiple interpretations, each illuminating different aspects of why integration remains elusive despite substantial research investment.

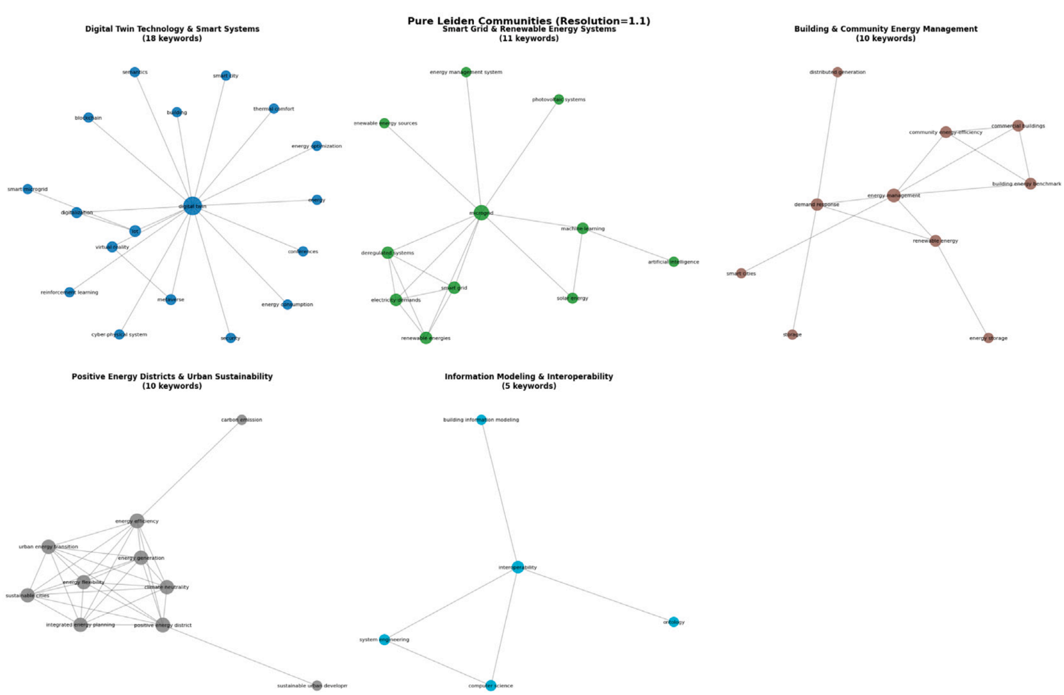
The maturity gradient problem. Communities exhibit dramatically different maturity levels, creating mismatched incentives for integration. High-density communities (Positive Energy Districts: 0.667; Smart Grid & Renewable Energy Systems: 0.309) represent established research traditions with standardized methodologies, shared benchmarks, recognized expertise hierarchies, and accumulated domain knowledge. This depth enables sophisticated within-domain progress but creates integration barriers: specialized vocabularies become opaque to outsiders, review processes favor incremental advances, and researchers optimize for within-community recognition. Consequently, no community is positioned to lead integration efforts.

Disciplinary boundaries and professional silos. Detected communities align with traditional academic disciplines and professional domains—building science, electrical engineering, urban planning, computer science—each maintaining separate institutional structures including degree programs, journals, and career pathways. These structures create disincentives for integration work requiring fluency across multiple domains.

Incompatible problem framing. Different communities conceptualize “district energy transition” through fundamentally different lenses emphasizing orthogonal dimensions. Building-focused research frames the problem as energy demand reduction: optimizing envelopes, Heating, Ventilation, and Air Conditioning (HVAC) systems, and occupant behavior to minimize consumption while maintaining comfort. Success metrics involve annual energy use intensity, lifecycle costs, and thermal performance. Grid-focused research frames the problem



(a) Abstract-based network ($\gamma = 1.0$)



(b) Keyword-based network ($\gamma = 1.1$)

Fig. 5. Community structures identified by Leiden algorithm. (A) Ten communities detected in abstract-based network. (B) Five communities detected in keyword-based network. Colors distinguish different research communities.

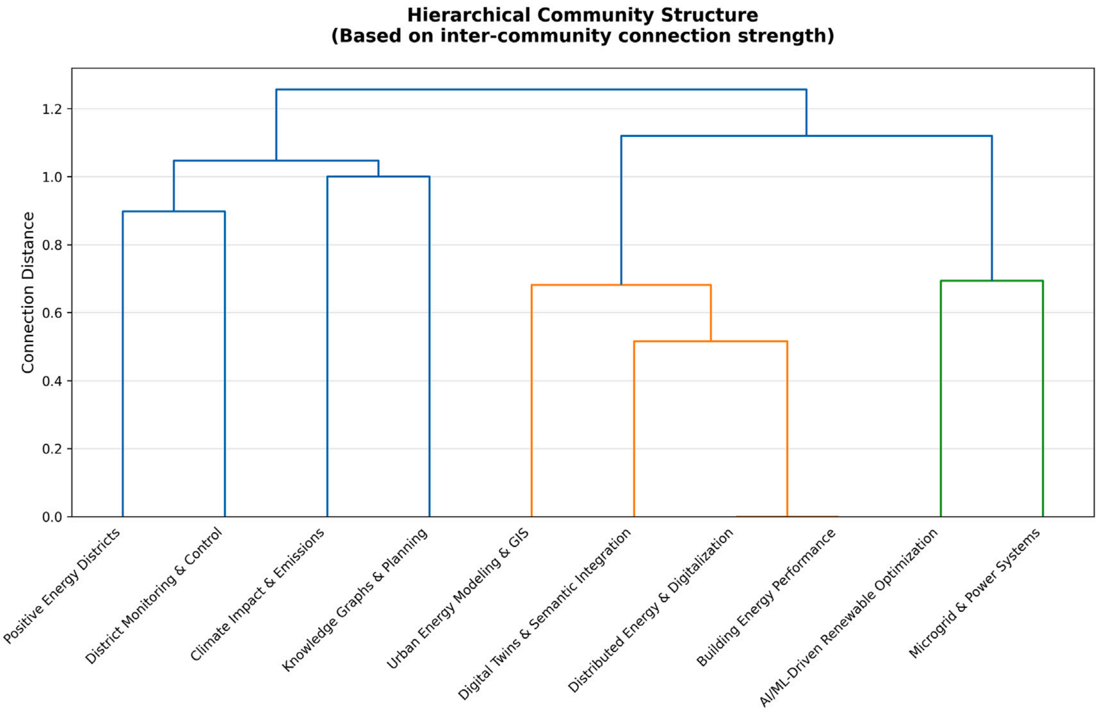


Fig. 6. Hierarchical clustering dendrogram of abstract-level communities based on inter-community connection strengths using Ward's linkage method.

as reliability maintenance: managing voltage regulation, frequency control, and stability amid variable renewable generation. Success metrics involve power quality indices, outage duration, and stability margins. These frames are not contradictory—buildings must reduce consumption AND grids must maintain stability—but they are orthogonal, emphasizing different aspects of the same physical system. Without explicit reconciliation, researchers naturally pursue their own frame's objectives, developing terminology and methods specific to their problem definition rather than seeking common ground.

The integration research dilemma. Integration research faces a fundamental coordination problem revealed by network structure. To demonstrate value, integration technologies (digital twins, knowledge graphs, semantic models) must solve problems important to application domains. But application domains define problems using their own terminology and methods, which integration researchers often lack expertise in. Integration research focuses on *tools* (data pipelines, ontologies) without engaging *problems* (coordinating building retrofits with grid planning), explaining both the Digital Twin community's low internal density and Knowledge Graphs' isolation from application domains.

5. Digital twin components for district energy transition

Building on the conceptual foundations established in Section 2, this section examines how DT architectures can support district energy transitions.

Commonly, a DT is characterized by three primary elements: a physical model—the physical twin that the digital twin seeks to replicate, a virtual model, and the linkage between the two, which can be data exchange, analysis, and communication platforms [42–44]. As it evolves and based on the applications of DT, more elements or components are introduced [45,46].

In this study, five components are considered as follows: 1) Physical world 2) DT 3) Data Infrastructure 4) Analysis & Simulation Engine 5) Interactive Stakeholder Gateway. In Fig. 7, the interactions between these components are shown.

The Physical World component—encompassing district energy infrastructure and conceptual frameworks—forms the foundation for DT architecture, as examined in Section 5.1.

5.1. Two paradigms in district energy transitions

District-level energy transitions manifest through various conceptual frameworks, each with distinct origins and priorities. Two prominent paradigms emerged from the literature: microgrids and Positive Energy District (PED)-type approaches [47].

Microgrids originate from electrical engineering perspectives, emphasizing grid architecture, power quality, and operational reliability [29,48]. They treat buildings as controllable loads within electrical networks, optimizing for grid stability and resilience [21]. Recent developments incorporate demand-side management and building HVAC systems as flexibility resources [49–51].

PED-type approaches—including Positive Energy Districts, Near-Zero Energy Districts, and Zero Energy Communities—emerge from sustainable urban planning, prioritizing net-positive or net-zero energy balance through building performance improvements and renewable integration [19,52–56]. These approaches view the grid as infrastructure for energy exchange, focusing on building stock improvement and annual energy balance.

5.1.1. Paradigm characteristics and origins

Examining Microgrids (MGs) alongside PEDs offers valuable insights, given their similarities in striving for energy autonomy and sustainability within buildings and district settings. Table 1 compares key characteristics of microgrids and PED-type approaches across multiple dimensions, clarifying their distinct priorities and potential complementarities.

These distinctions shape DT development. Microgrid applications emphasize grid topology modeling and real-time control, while PED applications prioritize building physics modeling and strategic planning [71,72].

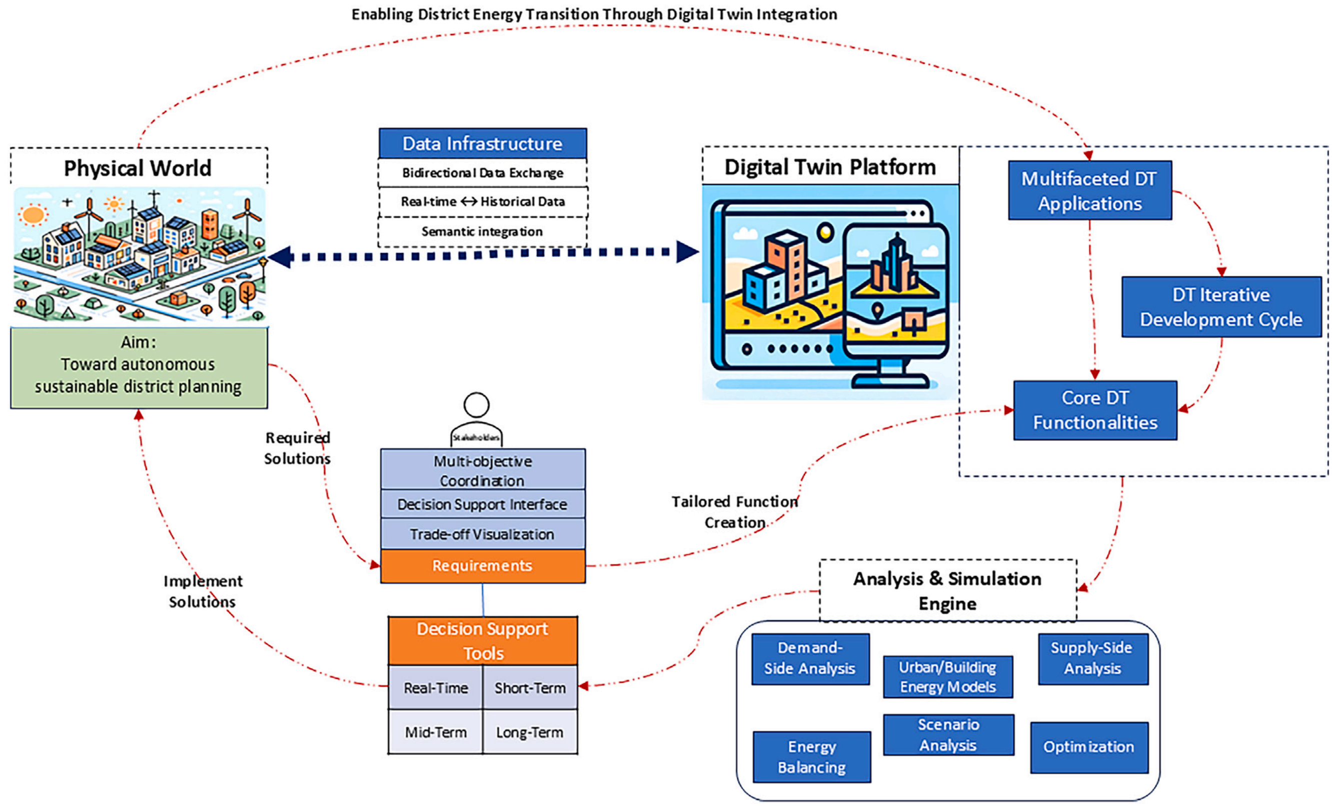


Fig. 7. Key components in development of a framework for employing DT in district-level energy planning.

5.1.2. Applications organized by paradigm

DT applications in energy management can be categorized by their paradigm alignment. Table 2 organizes applications from the reviewed literature according to primary focus area, revealing distinct application portfolios serving different objectives and stakeholder needs.

Applications align with paradigm priorities: PED-focused (urban planning, sustainability assessment [1,73,74]), MG-focused (power systems, predictive maintenance [21,22,69,78]), or cross-cutting ("Both"), which serve foundational functions bridging operational and strategic objectives [29,53,79,85,86]. Benefits span operational, strategic, economic, and technical dimensions.

5.2. Value propositions and benefits

The benefits realized through DT implementation reflect application priorities and paradigm alignment. Table 3 organizes benefits by type, showing how different value propositions serve distinct stakeholder needs and planning horizons.

Subsequent sections examine data infrastructure, functional evolution, modeling and analysis methods, technology platforms, and implementation considerations for integrated planning.

5.3. Economic viability of digital twin-enabled district coordination

Economic viability ultimately determines DT implementation feasibility despite demonstrated operational and environmental benefits (Table 3).

Traditional distribution network reinforcement follows lumpy investment patterns, requiring large capacity additions carried out in costly increments with extended periods of underutilized capacity [12]. These investments recover costs through regulated rate increases regardless of utilization, offering limited flexibility as district requirements evolve. DT systems enable alternative pathways where distributed generation, storage, demand response, and energy efficiency serve as alternatives to grid capacity enhancement [12]. Beyond deferring physical infrastructure, DT implementations deliver maintenance cost reductions and enhanced decision-making capabilities across system lifecycles [2].

Empirical evidence demonstrates feasibility across multiple scales. At the building level, Kaewunruen et al. [79] showed DT-enabled evaluation achieving 6.76% energy demand reduction through BIM-based retrofit assessment, with investment requirements of £111,000–£446,000 yielding 23-year payback periods for integrated net-zero conversions in existing UK buildings. At the network scale, Poudineh and Jamasb [12] demonstrate coordination value through ISO New England's capacity auction, where demand-side resources generated $24 million in ratepayer savings by reducing market clearing prices. Neumann et al. [52] provide systematic feasibility assessment methodologies for positive energy districts across Vienna urban typologies, incorporating economic, financial, legal, and regulatory aspects. Policy validation emerges through the U.S. Department of Energy's $65 million allocation for "Connected Communities" transactive energy demonstrations [14], signaling federal recognition of coordination approaches as credible pathways for district-scale transformation.

5.4. Functional evolution and maturity

DT capabilities evolve across five functional levels, each enabling progressively sophisticated applications [20,46]:

1. Informative function: Provides basic information about the state of a system or component.
2. Diagnostic function: Offers insights into why certain states are occurring.
3. Predictive function: Anticipates future states and potential issues based on current and historical data trends.
4. Advisory function: Uses insights to recommend actions for achieving desired outcomes or preventing undesired ones.

Table 1
Comparison of microgrids and PED-type approaches*.

Category	Microgrids	PED-type approaches	Similarities/differences
Primary origin	Managing renewable energy intermittency and ensuring energy security. Modern concept emerged in 1990s [57–59]	Climate mitigation, decarbonization, and sustainable urbanization. Driven by European Union (EU) SET Plan Action 3.2 [20,47,52,60,61]	Diff: PEDs emerge from policy and climate targets; MGs from power system stability needs
Scale	Localized power systems with capacities from few kilowatts to multiple megawatts. Electrical boundary defines scale [28,58]	Urban districts or neighborhoods with connected buildings. Upscales energy solutions from single-building to complex district level [19,20,55]	Diff: PED scale tied to geographical urban area; MG scale tied to electrical distribution boundary
Energy target	Reliable power supply and resilience during outages [59,62]	Net positive energy balance and net zero greenhouse gas (GHG) emissions on annual basis [19,20,48]	Diff: PED mandates environmental targets with annual energy surplus; MG prioritizes electrical reliability and islanding capacity
Grid relationship	Operates on-grid or isolated (island mode). Acts as single controllable entity with seamless mode transitioning [29,59]	Active interaction with utility grid and District Heating Network (DHN). Types: Dynamic (bidirectional exchange), Virtual (external generation/storage), Autonomous (self-sufficient) [19,55,63,64]	Diff: MGs designed for isolated operation ensuring resilience; PEDs manage annual surplus/deficit via predefined grid exchange
Time horizon	Real-time scheduling and control due to renewable energy resource (RER) intermittency. Planning spans real-time to long-term expansion [29,57,65,66]	Annual energy accounting with seasonal variations. Life cycle planning considers Positive Energy Quotient (PEQ) Omega [20]	Diff: MGs emphasize rapid (sub-second) response for stability; PEDs rely on annual energy flow summation
Key technologies	Distributed Energy Resources (DERs), Battery Energy Storage System (BESS)/Energy Storage System (ESS), power electronic converters, control systems. IoT, AI/ML, and MODBUS protocols [22,49,59]	RESs, energy efficiency measures, ESS, EVs/Vehicle-to-Grid (V2G), DHN, and Information and Communication Technology (ICT) integration [4,47,53,67]	Sim: Both use RESs and ESS with ICT/IoT. Diff: PED explicitly incorporates multi-carrier urban infrastructure
Control focus	Reliable, secure, economic operation via hierarchical control (primary, secondary, tertiary). Frequency stability and voltage control prioritized [21,22,51,58]	Optimizing energy flow, resource sharing, and flexibility across urban infrastructure via Smart Energy Management System (EMS) to meet annual goals [52,55,67]	Diff: MG control centers on electrical stability and fast regulation; PED optimizes broader energy flexibility across urban systems
Planning priority	Resilience, reliability, system stability, and operational cost minimization [59,62,68]	High energy efficiency, local RESs supply, system flexibility optimization, and integrating urban, social, energy aspects [52,60,64]	Diff: PED framework is multi-domain (urban, social, energy); MG framework primarily electrical power operation
Economic model	Cost minimization and profitability via optimal scheduling. Revenue through energy arbitrage and demand response (DR) programs. Peer-to-peer (P2P) trading model [59,62,69,70]	Cost savings via efficiency and local generation. Shared ESS deployment, open market participation, surplus energy sales. Energy Community cooperative models [4,58,63,67]	Sim: Both seek financial benefits via optimal energy management and RER maximization. Diff: PED uses community cooperative models; MG focuses on operator efficiency
Stakeholder priority	Providing reliable, high-quality power to customers. Government, utilities, owners of critical facilities (military bases, hospitals, academic institutions) [59,62]	Ensuring social, economic, environmental sustainability for all inhabitants. Citizens, local authorities, Transmission System Operators (TSOs)/Distribution System Operators (DSOs), developers. High priority on engagement and social justice [19,52,71]	Diff: PED integrates citizen welfare into core definition and metrics; MG prioritizes technical reliability for critical loads and utility standards

Includes Positive Energy Districts, Near-Zero Energy Districts, and Zero Energy Communities

5. Autonomous function: The most advanced function, where the DT autonomously makes and implements decisions.

Application scales for DTs extend from elemental to enterprise levels. In energy management, this ranges from sub-building components to individual buildings, districts, urban areas, and beyond (Fig. 8). At district scale, convergence of building operators, grid utilities, and urban planners creates both complexity and opportunity for integrated infrastructure decisions.

DT complexity increases with functional advancement and application scale expansion. Current implementations in district energy management primarily demonstrate informative and diagnostic functions (levels 1-2), with emerging predictive capabilities (level 3). The progression toward advisory and autonomous functions (levels 4-5) remains largely theoretical at district scale, where coordination across multiple stakeholders complicates automated decision-making. This review focuses specifically on district-level applications, examining capabilities across these functional levels to identify pathways toward more sophisticated implementations.

5.5. Data infrastructure and management

Effective data infrastructure forms the foundation enabling DT capabilities to support district energy transitions. This infrastructure must reconcile heterogeneous data sources operating across distinct temporal scales while preserving domain-specific semantics essential for decision-making.

5.5.1. Semantic differences between domains

Building and grid systems characterize energy flows through fundamentally different conceptual frameworks. Building models emphasize thermal performance—envelope characteristics, HVAC efficiency, and thermal zone interactions [106,107]. Grid representations focus on electrical parameters—power flows, voltage profiles, and frequency stability [29,108]. These semantic differences manifest in data structures: buildings represented in Industry Foundation Classes (IFC) format contain geometric and thermal properties [87,98], while grid models characterize buildings as aggregated load nodes [81,109]. Converting between these representations—translating thermal characteristics into electrical flexibility or mapping grid constraints to building operations—typically requires custom implementations. Semantic technologies offer potential approaches. SAREF ontologies provide domain-neutral vocabularies, with SAREF4BLDG addressing building systems and SAREF4ENER capturing energy flexibility [42]. Knowledge graph architectures like Akroyd et al.'s Universal Digital Twin demonstrate multi-ontology integration, connecting OntoCityGML urban data with OntoPowerSys electrical representations through standardized SPARQL queries [103]. These implementations remain primarily research demonstrations, with widespread adoption not yet realized [20,98,110].

Table 2
Digital twin applications by domain and paradigm alignment.

Category	Specific application	Description	Paradigm	Refs
Urban development and planning	Urban System Monitoring and Predictive Analysis	In-depth monitoring and predictive analytics for urban infrastructure, emphasizing preemptive actions to mitigate potential system failures.	PED	[73]
	Strategic Urban Development Planning	Leveraging DT for effective strategic planning, incident response, and pattern assessment in urban environments.	PED	[74]
	Methodological Approach in Urban Planning	DT for planning, research, virtual experimentation, and testing in urban development, focusing on digital, ecological, and energy transitions.	PED	[1,75]
Infrastructure and construction	Smart City Optimization	Utilizing sensor data for real-time monitoring to optimize city services, urban living, and intelligent management and maintenance of civil infrastructures using DT.	Both	[74]
	Industry 4.0 and Construction 4.0 Applications	Data-driven management of physical processes in industry and construction, featuring decentralized, self-learning mechanisms.	Both	[53,76,77]
Technology integration	DT Interoperability	Ensuring interoperability and secure sharing of models and data among different DT services.	Both	[29]
	Incorporation of Advanced Technologies	Integration of AI, IoT, cloud computing, 5G, Big Data, Blockchain, BIM, and City Information Modelling for enhancing urban environments.	Both	[1]
Energy sector applications	Power System Operations and Smart Grids	DTs as virtual mirrors of power systems for enhancing demand-side management, energy distribution efficiency, and integration of renewable energy sources into power grids using forecasting tools.	MG	[78]
	Urban sustainability and planning	Support for climate adaptation and proactive planning in PEDs, assessing the impact of new strategies, aiding in construction decision-making, and reducing waste and inefficiency.	PED	[20]
	Near Zero Energy Districts (nZED) and battery energy storage systems	Simulation of renewable energy integration into districts, aiding in the transformation toward nZEDs, and assessing the health and efficiency of batteries in MGs.	Both	[21,53,79]
	Predictive maintenance and optimization in MGs	Using DTs for forecasting potential failures and enhancing MGs operations for planning, maintenance, control, fault diagnosis, and real-time monitoring.	MG	[21,22,69]
	Innovative control systems and energy sector revolution	Development of advanced automated control systems for reducing manual interventions, connecting digital platforms to real systems for improved energy system management, and promoting sustainability.	MG	[2,69,80]
Energy management and optimization	Energy System Management and Urban and District Planning	Development of DT models for energy systems in smart cities, including City Information Modelling, and BIM-based toolkit for building renovation and urban-scale building energy modeling.	PED	[73,81,82]
	Renewable energy optimization and grid and MGs operations	Modeling renewable energy systems, optimizing Photovoltaic (PV) system and wind turbines installation, real-time DT for grid operations, and management of battery energy storage systems.	MG	[83,84]
	Energy demand response and simulation, forecasting	Distributed energy management strategy, demand-side management in smart MGs, simulation of energy performance, and forecasting of renewable energy sources.	Both	[85,86]
	Sustainability, Environmental Impact and Decision Support, Optimization	Enhancing sustainability in smart buildings, designing energy-resilient neighborhoods, decision-making support for energy systems, and multi-objective optimization in HVAC systems.	PED	[87,88]
	Innovative Energy Solutions	Development of a metaverse in the Energy Internet, application of AI, IoT, and DT technologies in campuses, and implementation of innovative energy management models.	Both	[89,90]

5.5.2. Temporal coordination across planning horizons

Energy systems operate across nested temporal scales from sub-second grid regulation to multi-decade infrastructure planning [12,87,108]. Data architectures typically optimize for specific timescales—SCADA systems for real-time grid stability, smart meters for operational dispatch, and building simulations for long-term planning [29,109]. Building HVAC optimization yields operational efficiency improvements [87], yet connecting operational patterns to long-term infrastructure strategies remains uncommon. Strategic planning typically projects demand using historical trends while building evolution models operate separately [111]. Linking these temporal scales would require preserving sufficient operational detail while enabling meaningful decade-scale projections—a data architecture capability that implementations identify as necessary but rarely demonstrate systematically [112,113].

5.5.3. Standards within and across domains

Each domain has developed mature standards reflecting operational priorities. Building domains widely adopt IFC for geometric representation and system specifications [87,98], City Geography Markup Language (CityGML) for 3D urban models [106], and various formats for energy simulation exchange. Grid operations rely on Common Information Model (CIM) (IEC 61,970/61,968) for topology and equipment representation [114]. Geospatial frameworks provide spatial context through OGC standards—WFS for vector data, SensorThings Application Programming Interface (API) for IoT streams [106,115].

These within-domain standards achieve widespread use and enable effective data exchange among domain specialists. Cross-domain coordination presents different challenges. Santhanavanich et al. demonstrate spatial data infrastructure connecting CityGML building models with SensorThings API energy data streams for district-scale analysis [106]. BIM-GIS integration reveals how geography influences energy flows and infrastructure constraints [9,43]. Process modeling through Unified Modeling Language (UML) captures system evolution—how building retrofits propagate through load profiles and grid impacts [103,114].

Semantic alignment between standards remains limited despite various approaches. Bjornskov and Jradi [42] show SAREF4BLDG enables

Table 3
Benefits of integrating digital twins in the energy sector.

Benefit type	Specific benefit	Description	Refs
Operational excellence	Grid Resilience	DTs contribute to the stability and reliability of energy grids by facilitating advanced simulation and analysis, thereby enhancing the resilience of energy systems to fluctuations and disruptions.	[58,91,92]
	Forecasting, Simulation	DTs provide capabilities for accurate forecasting, scenario modeling and what-if analyses, crucial for efficient operation and strategic planning.	[93,94]
	Data-Driven Decision Making	Equipping professionals with the tools for proactive decision-making, DTs enable the optimization of system and network operations through data-driven insights, including the prediction of system failures.	[76,95]
	Building Operations	DTs, in conjunction with other digital technologies, streamline building operations. They address and overcome the limitations of traditional approaches, facilitating seamless management practices.	[96]
Strategic planning	Decision Making, Planning	DTs support integrated decision-making that validates long-term infrastructure plans against operational constraints and evaluates intervention sequences across temporal scales.	[1,95]
	Non-Wire Alternative Evaluation	Enables systematic techno-economic comparison of building retrofits, Distributed Energy Resources (DERs), and demand response against traditional grid upgrades, revealing cost-effective deferral opportunities.	[12]
	Building Energy Assessment	DTs significantly improve the precision of energy assessments for buildings. By integrating with other technological solutions, DTs offer detailed insights into energy efficiency, enabling more accurate evaluations and informed decision-making.	[97–99]
Economic value	Cost Reduction	DTs lead to notable reductions in operating costs, thereby achieving energy savings and improving the economic viability of energy systems.	[89,93,100]
	Market Innovation	DTs provide the foundation for new-age market structures, especially for distributed RESs and enable the emergence of efficient energy market structures.	[20,42]
Sustainability & environment	Environmental Impact	Supporting the goals of decarbonization and the integration of RESs, DTs play a significant role in advancing towards low-carbon objectives.	[43,79]
	Renewable Energy Optimization	By modeling and predicting the behavior of renewable energy systems, DTs are instrumental in their integration and optimization, ensuring effective use of renewable resources.	[101]
	Smart Urban Development	At the forefront of smart urban development, DTs contribute to the intelligence and evolution of urban infrastructure. They support real-time decisions on energy performance, pushing the boundaries of what's possible in smart buildings and cities.	[74,102]
Technical integration	Interoperability	Enhancing the coordination and integration of energy assets, DTs support cross-domain interoperability and are essential for comprehensive urban energy planning.	[75,103]
	Security, Resilience	DTs improve situational awareness and ensure the resilient operation of energy management systems.	[1]
Innovation	Future Development	Drives future advancements in energy systems and supports the evolution of innovative energy management models.	[44,104,105]

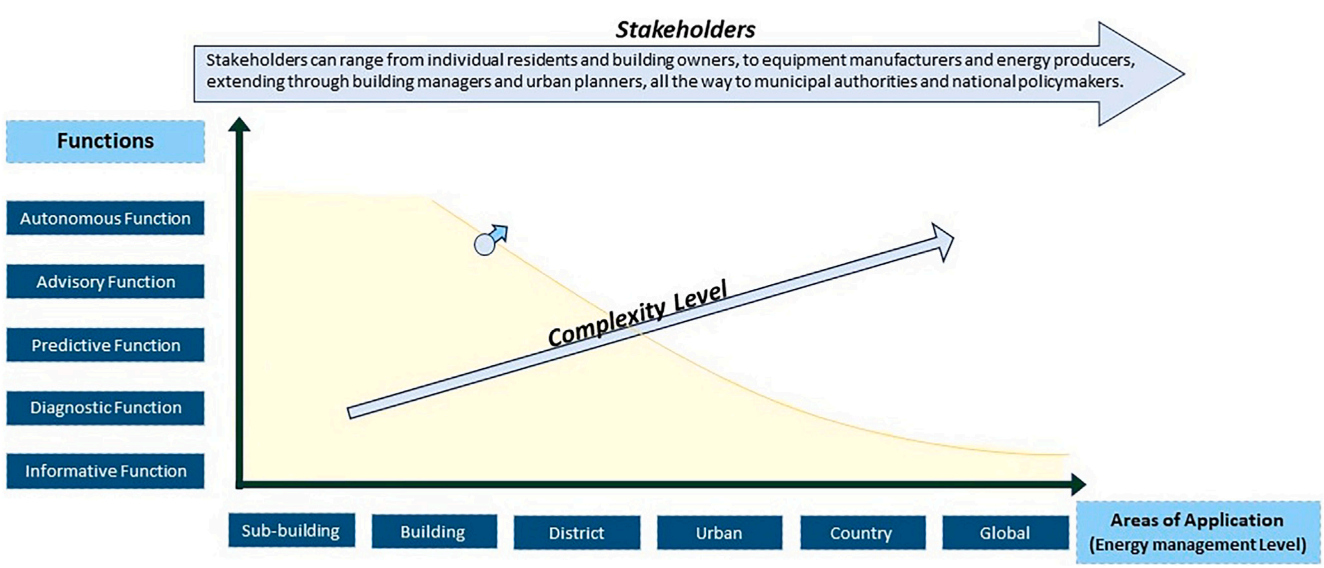


Fig. 8. Mapping the evolution and potential of DT functions in energy management.

"almost direct mapping between IFC and SAREF," yet components like `s4bldg:SpaceHeater` lack behavioral models needed for simulation. Akroyd et al. [103] federate OntoCityGML with OntoPowerSys through SPARQL queries, enabling cross-domain traversal from building systems to grid infrastructure. Dabirian et al. [75] employ central data models with Import/Export Factories as interface layers, prioritizing implementation practicality. Extending CIM for distributed energy systems reveals ontology inconsistencies requiring continuous harmonization with proprietary systems [116].

These cross-domain implementations remain demonstrations rather than established practice. Smart meter infrastructure, while serving multiple purposes [106,117], typically operates within single domains.

5.5.4. Data quality and governance requirements

Application requirements shape data precision needs: revenue-grade metering requires ±0.5% accuracy, while building energy monitoring accepts ±2–5% for operational insights [49,107]. Urban-scale implementations balance computational efficiency with modeling fidelity when processing thousands of buildings [115,118]. Archetype-based approaches enable district analysis when detailed building data remains unavailable [118,119]. Reconciling competing stakeholder interests presents fundamental governance challenges. Municipalities, private operators, and prosumers maintain distinct priorities regarding data ownership, curation, quality, and liability—questions that remain active research areas [103]. Distributed architectures offer a pathway forward, enabling data owners to retain hosting control while defining granular access rights [103]. This approach becomes increasingly critical given escalating security threats: cyberattacks on European energy systems doubled between 2020–2022 [120]. Beyond external threats, cloud-based architectures introduce API vulnerabilities and access management complexities [74,75]. Privacy protections remain essential when combining building-level sensor streams with grid operational information, particularly for prosumer consumption patterns [10,58,74]. Blockchain-based data management offers promising mitigation through enhanced traceability and tamper-resistant records, increasing trust for authorized information sharing [29]. These governance challenges manifest differently across planning horizons. Strategic planning can leverage building archetypes and simulated data to address privacy concerns, while operational deployment demands secure historical consumption data that may be incomplete or proprietary. Knowledge graph architectures within DT frameworks enable federated queries across distributed data sources, preserving ownership boundaries through semantically explicit access controls. As state-sponsored cyberattacks intensify, such distributed governance models become essential for maintaining operational security while enabling cross-domain coordination.

5.5.5. Integration requirements

Three integration requirements emerge: semantic translation between thermal and electrical representations, temporal aggregation preserving operational detail while enabling long-term analysis, and coordination mechanisms building on existing standards rather than requiring replacement. Current implementations demonstrate sophisticated capabilities within individual domains. Cross-domain coordination frameworks that systematically address these requirements represent an area where technical demonstrations exist but widespread practice has not yet developed. The challenge appears less technical than organizational—requiring coordination among stakeholders who currently operate with distinct priorities, timescales, and success metrics.

5.6. Modeling and analysis methods

5.6.1. Physics-based and data-driven energy modeling

Energy modeling employs two complementary paradigms. Physics-based models use first-principles equations for building thermal dynamics, HVAC systems, and power flow analysis, providing mechanistic understanding but requiring detailed physical parameters and enabling prediction under conditions beyond historical experience [20,109,117,121,122]. Data-driven models leverage machine learning for forecasting, occupancy detection, and load prediction, offering adaptive learning from operational data without explicit physics representation [20,24,117,123].

Building-focused applications couple thermal simulation with control optimization, while grid-focused implementations integrate power flow analysis with operational monitoring [29,109,122]. Hybrid frameworks combining both paradigms prove effective for strategic planning, where long-term evolution requires mechanistic understanding while operational patterns inform model calibration [2,109]. Co-simulation interfaces enable coupling between domain-specific tools, allowing evaluation of building improvements' effects on grid infrastructure across timescales [20,109]. Building thermal models achieve strong predictive accuracy when validated against utility data, though performance degrades in rapidly electrifying districts where technology adoption alters load patterns [3,109].

Renewable generation modeling combines resource characterization with stochastic forecasting [7,83]. Grid integration analysis couples generation profiles with power flow models, revealing how distributed renewable injection creates reverse power flows challenging traditional planning [3,109,124]. Storage system models optimize renewable utilization through learning-based approaches [20,67].

5.6.2. Multi-domain performance indicators

DTs model diverse performance dimensions reflecting multi-stakeholder priorities. Thermal comfort modeling maintains indoor conditions while optimizing HVAC energy consumption [24,87]. Grid stability analysis simulates voltage regulation and frequency control, with power flow models identifying where building-level interventions alleviate feeder constraints [3,49,109]. Emissions quantification tracks operational carbon footprints, with district implementations demonstrating substantial reductions through coordinated retrofits and renewable integration [20,109]. Economic optimization employs lifecycle cost analysis comparing infrastructure alternatives [12,21,67], while predictive maintenance applies anomaly detection to equipment sensor streams [2,7]. Flexibility assessment quantifies load-shifting potential and demand response capacity, revealing grid service value from building thermal mass and storage systems [20,50]. This multi-indicator approach enables holistic evaluation recognizing trade-offs between energy efficiency, comfort, reliability, and economic viability [24,87].

5.7. Scenario planning, optimization, and decision support

Strategic planning for district energy transitions requires evaluating alternatives across multiple temporal scales and uncertainty dimensions. DTs support this through scenario analysis, optimization methods, and demand flexibility coordination.

5.7.1. Temporal scales and decision contexts

Applications span real-time operational control through strategic infrastructure planning. Real-time control addresses grid frequency regulation and building HVAC optimization [24,49,87,108]. Short-term scheduling optimizes day-ahead generation-storage-demand coordination using load and renewable forecasts [20,67,125]. Mid-term planning addresses seasonal storage strategies and maintenance scheduling across weather patterns [2,20,126]. Strategic infrastructure planning evaluates building retrofit sequences, distributed resource deployment, and grid reinforcement timing over multi-decade horizons [109,111,126]. These scales interconnect through hierarchical frameworks where strategic commitments constrain operational flexibility, while operational insights—such as recurring constraint violations—inform infrastructure priorities [3,29].

5.7.2. Scenario analysis approaches

Scenario analysis serves distinct purposes across planning contexts. Design-phase evaluation explores technology alternatives, installation sequences, and investment timing before implementation. Johari et al. demonstrate systematic comparison of retrofit scenarios across building portfolios, evaluating options by economic performance, demand impacts, emissions reductions, and grid effects to identify cost-effective intervention sequences [12,109]. Operational scenario planning simulates system response to disturbances—weather changes, equipment failures, renewable variability—developing contingency protocols and validating control strategies [69,108,127,128]. Microgrid implementations employ scenario-based stress testing to ensure reliability under diverse conditions [29,49]. Real-time scenario analysis supports operational decisions, with "what-if" queries informing dispatch within short response windows [24]. Strategic scenarios explore long-term implications of regulatory changes, technology evolution, and climate adaptation [1,17,111,126]. Knowledge graph approaches enable comparative evaluation of alternative futures without overwriting baseline scenarios, allowing exploration of policy combinations and cascade effects across coupled systems [103,129]. Scenario analysis proves valuable when uncertainties exceed historical variability—as electrification transforms load profiles, historical patterns become unreliable predictors [109]. Simulating diverse futures under explicit assumptions bounds decision risks and reveals robust strategies performing acceptably across plausible conditions [31,32].

5.7.3. Optimization methods and algorithms

Method selection depends on problem structure, time horizon, and model characteristics. Mixed-Integer Linear Programming (MILP) addresses scheduling problems combining discrete decisions with continuous variables, proving effective for battery dispatch, HVAC control, and demand response coordination where system models are well-defined [2,20,24,110]. Model Predictive Control (MPC) extends this to receding-horizon frameworks, re-optimizing as forecasts update and demonstrating energy savings in building applications [24,87,130]. Reinforcement Learning (RL) learns optimal sequences where interventions create path dependencies [65]. RL addresses problems where explicit models prove intractable or environments exhibit non-stationary dynamics, learning optimal policies through simulated experience [8,67,127,131]. RL proves effective for adaptive control under renewable uncertainty, though requiring substantial training and hyperparameter tuning [67,105,132,133]. Genetic Algorithms and metaheuristics tackle non-convex design problems—renewable system sizing, building retrofit selection, topology optimization—where gradient-based methods fail [69,87,134]. Multi-objective optimization explicitly balances competing goals through Pareto frontier generation, revealing trade-offs essential for stakeholder negotiation [24,87]. Optimization effectiveness depends critically on data quality—incomplete or biased operational data produces unreliable strategies regardless of algorithmic sophistication [135].

5.7.4. Demand management strategies

Demand-side flexibility represents a critical resource for balancing renewable variability and deferring infrastructure upgrades. Building-level implementations activate thermal mass and HVAC flexibility through automated load shifting, while microgrid coordination aggregates heterogeneous resources—batteries, controllable loads, EVs—for optimized dispatch [24,49,85,136]. District-scale orchestration demonstrates infrastructure value: systematic activation across aggregated buildings reduces substation peak loading, potentially deferring grid upgrades through distributed interventions rather than centralized infrastructure [12,17,109]. DTs enable this coordination by forecasting flexibility availability and simulating aggregated impacts on feeder voltages and transformer loading [3,29].

5.8. Technology platforms and visualization

5.8.1. Technology and tools

DT implementations employ commercial platforms, open-source toolchains, and emerging integration frameworks. Tool selection reflects domain priorities, with distinct ecosystems across building and grid domains and fragmented cross-domain integration [2,20,117].

Building domain toolchains prioritize geometric modeling and thermal simulation. Autodesk Revit dominates as the BIM foundation, storing building topology, material properties, and equipment specifications via Industry Foundation Classes (IFC) export [79,98,117]. EnergyPlus provides physics-based thermal simulation computing hourly HVAC loads through Conduction Transfer Functions [20,117]. TRNSYS extends capabilities to district heating networks and multi-zone analysis, with BCVTB/FMI co-simulation enabling building-grid coupling at 15-minute synchronization intervals [20,24].

Grid domain platforms emphasize power flow analysis and operational control. MATLAB/Simulink dominates microgrid implementations through Simscape Power Systems for AC/DC network modeling and rapid controller prototyping, with OPAL-RT enabling hardware-in-the-loop validation [29,30,93]. OpenDSS performs distribution grid power flow calculations under unbalanced three-phase conditions [20,109]. Commercial optimization solvers (GAMS, Gurobi, CPLEX) handle unit commitment and economic dispatch formulations [29].

Cross-domain integration platforms address building-grid silos through semantic knowledge graphs and unified data models. Neo4j knowledge graph database enables the World Avatar project's "parallel worlds" scenario analysis, storing alternative configurations as queryable subgraphs [103,112]. Cloud platforms (AWS, Azure, Google Cloud) provide computational infrastructure for district-scale simulations, with InfluxDB managing IoT sensor streams at 1–15 minute granularity [2,24]. Web-based visualization frameworks enable stakeholder coordination across organizational boundaries [84,119].

Commercial DT platforms offer integrated solutions with varying domain specialization. Leading city-scale providers (Autodesk, Esri, Bentley, Cityzenith, Dassault Systèmes, Siemens) target urban planning and infrastructure management [20], while energy sector platforms (SPHERE, BuildingMinds, Siemens Building Twin) embed domain-specific analytics for renewable forecasting and HVAC optimization [2,137]. Tools like ENECO2Calc enable municipality-level energy transition scenarios but operate at aggregated sectoral levels rather than building-by-building resolution needed for targeted infrastructure planning [126].

Tool selection involves trade-offs between flexibility and integration complexity. Open-source toolchains (EnergyPlus + OpenDSS + Python) enable deep customization but require substantial development effort, while commercial platforms accelerate deployment at significant licensing costs [24,117]. However, neither approach adequately addresses sequential intervention optimization—current tools excel at *what* to install but lack frameworks for determining *when* and *in what order*, the temporal dimension critical for Non-Wire Alternative evaluation.

5.8.2. Visualization technologies

Visualization architectures reflect dual purposes: technical monitoring for operators and stakeholder communication for planning processes. Domain differences shape technology choices—microgrids employ 2D dashboards for power flow monitoring, while district energy planning requires 3D visualization to capture building geometry, solar access, and spatial relationships affecting energy performance [20,115].

Operational dashboards prioritize real-time data density and responsive updates. Grafana dominates as open-source framework, querying InfluxDB time-series databases to display building energy consumption, renewable generation, and grid metrics with sub-minute refresh rates [20,24]. Microgrid control rooms employ SCADA-style single-line diagrams showing transformer loading and voltage profiles as animated 2D schematics [9,29]. Web-based interfaces (D3.js, Chart.js) enable remote monitoring through REST APIs [24,112].

Stakeholder-specific interfaces balance technical detail against accessibility. Building managers receive simplified mobile displays showing energy costs and comfort metrics, while grid operators access detailed topology exposing transformer status and power flows [3,24]. Urban planners interact through scenario comparison interfaces displaying alternative buildout strategies—contrasting capital costs, carbon trajectories, and grid impacts—rather than raw simulation outputs [79,109].

A key limitation: 2D electrical schematics obscure spatial interdependencies essential for district planning, masking geographic load patterns that create localized constraints [109,115].

5.9. Implementation considerations

5.9.1. Validation and adaptive control

Validation strategies differ by application context. Annual energy predictions compare simulated consumption against utility billing data through multi-month calibration periods [109]. Operational control applications validate against submetered sensors at higher temporal resolution [20,24]. Power flow calculations verify against standardized test networks before field deployment [29,112,117], with field pilots comparing predictions against operational measurements to qualify systems for production use [3]. Coupled thermal-electrical models require end-to-end verification against utility measurements [20,109].

Key Performance Indicators (KPIs) quantify validation accuracy and operational effectiveness across energy systems. Uspenskaia et al. define temporal alignment metrics including Onsite Energy Ratio, Annual Mismatch Ratio, Maximum Hourly Surplus, and Maximum Hourly Deficit for Positive Energy Districts [71]. Shen et al. specify photovoltaic system KPIs such as Self-Consumption, Self-Sufficiency, and Levelized Cost of Electricity for techno-economic optimization [137]. Xu and Liu introduce demand-side management metrics including PAR Improvement Percentage and Wait Time Reduction to balance technical optimization with user satisfaction [138]. Bâra and Oprea define community-level indicators such as Self-Sufficiency Index, Self-Consumption Index, and Fairness Index for Energy Communities [139]. These metrics enable continuous performance monitoring, optimization benchmarking, and cross-system comparison.

Bidirectional architectures enable DTs to monitor systems and execute control commands. Sensor data streams at intervals matching control requirements, with building systems updating at minute intervals and grid variables at sub-second frequencies [24,29,117]. Optimization algorithms compute setpoint adjustments executed by building management and grid control systems [24,29]. Distributed implementations deploy edge agents that execute control autonomously while receiving objectives from centralized platforms [29,50].

Adaptive mechanisms maintain model accuracy as systems evolve. Predictive controllers re-solve optimization problems as forecasts update and conditions change [24,87]. Machine learning components retrain on recent operational data at intervals preventing degradation as patterns shift [20,67,133,137]. Anomaly detection algorithms flag sensor malfunctions or model drift when errors exceed thresholds [2,7].

5.9.2. Stakeholder coordination requirements

District energy transitions engage multiple actors with distinct priorities requiring coordination mechanisms. Grid operators prioritize infrastructure cost management, building owners focus on investment returns, urban planners pursue emissions targets, and residents expect maintained comfort [2,12,20,24,109,141].

Coordination approaches span centralized utility programs to distributed market-based platforms [3,12,14]. Information architectures employ privacy-preserving techniques and standardized interfaces enabling cross-organizational analytics [3,103,112]. Regulatory frameworks increasingly specify performance metrics and permit utilities to fund customer-side efficiency when cost-effective [12,141]. Implementation requires governance across district managers, building operators, utilities, planners, and community representatives [2].

6. Toward integrated district energy planning: a framework approach

This section presents an integrated framework that addresses three coordination gaps identified in Sections 4.1–Section 5: semantic integration across domains, temporal coordination across planning horizons, and sequential intervention optimization. Rather than replacing domain-specific tools, the framework provides integration infrastructure enabling existing capabilities to inform coordinated district energy planning.

6.1. Framework rationale and architecture

Network analysis (Section 4.1) revealed isolated building and grid communities despite critical interdependencies, while systematic review (Section 5) documented mature capabilities (knowledge graphs, coupled simulation, sequential optimization) that rarely integrate for coordinated planning.

Four interconnected components address this integration gap:

1. Knowledge graph foundation provides semantic data integration, linking building properties, grid topology, and operational data through standardized ontologies (Section 6.4).
2. Coupled simulation engine enables temporal coordination, linking real-time operations with strategic planning across multiple timescales (Section 6.5).
3. Sequential optimization captures path dependencies where intervention order fundamentally shapes outcomes (Section 6.6).
4. Stakeholder platform reconciles competing objectives across grid operators, urban planners, building owners, and policymakers (Section 6.7).

Fig. 9 illustrates the framework architecture spanning five layers. The *Physical World* (bottom) encompasses district buildings, electrical networks, and DERs. The *Data Infrastructure* provides bidirectional exchange between physical systems and digital representations. The *DT Platform* (center) integrates the four components: Knowledge Graph Foundation for semantic integration, Coupled Simulation Engine for temporal coordination, Sequential Optimization for intervention pathways, and Stakeholder Platform for decision support. The *Analysis & Simulation Engine* executes computational workflows, while the *Stakeholder Gateway* (top) provides role-specific interfaces. Feedback loops between layers enable continuous refinement: operational data improves models, simulation results inform optimization, and stakeholder input guides evolution, transforming the framework from static planning tool to an adaptive management system.

6.2. Framework operation: an illustrative example

To illustrate how framework components operate in concert, consider the following district decarbonization scenario.

Consider a 200-building district planning decarbonization over 10+ years. The Knowledge Graph integrates heterogeneous data—building geometries (IFC), electrical topology (CIM), spatial relationships (CityGML), and sensor streams—enabling cross-domain queries like “which buildings on Feeder F-12 have solar potential exceeding 50kW?”.

Co-simulation tools couple building energy models with power flow analysis through standardized API, enabling automated iteration: Building retrofits generate new load profiles → Power flow reveals grid impacts → Constraint violations trigger building intervention refinement. Multiple configurations execute in parallel, exploring intervention combinations at scale.

Sequential optimization employs RL to discover effective intervention sequences across domains. The agent selects actions—building envelope retrofits, HVAC electrification, rooftop solar deployment, community battery installation—balancing multi-dimensional rewards: capital costs, CO_2 reductions, thermal comfort, and grid reliability. Constraints include feeder capacity limits and import/export thresholds.

The agent trains across diverse scenarios capturing demand, technology, and policy uncertainties. Through thousands of simulated district futures, the system learns robust strategies for

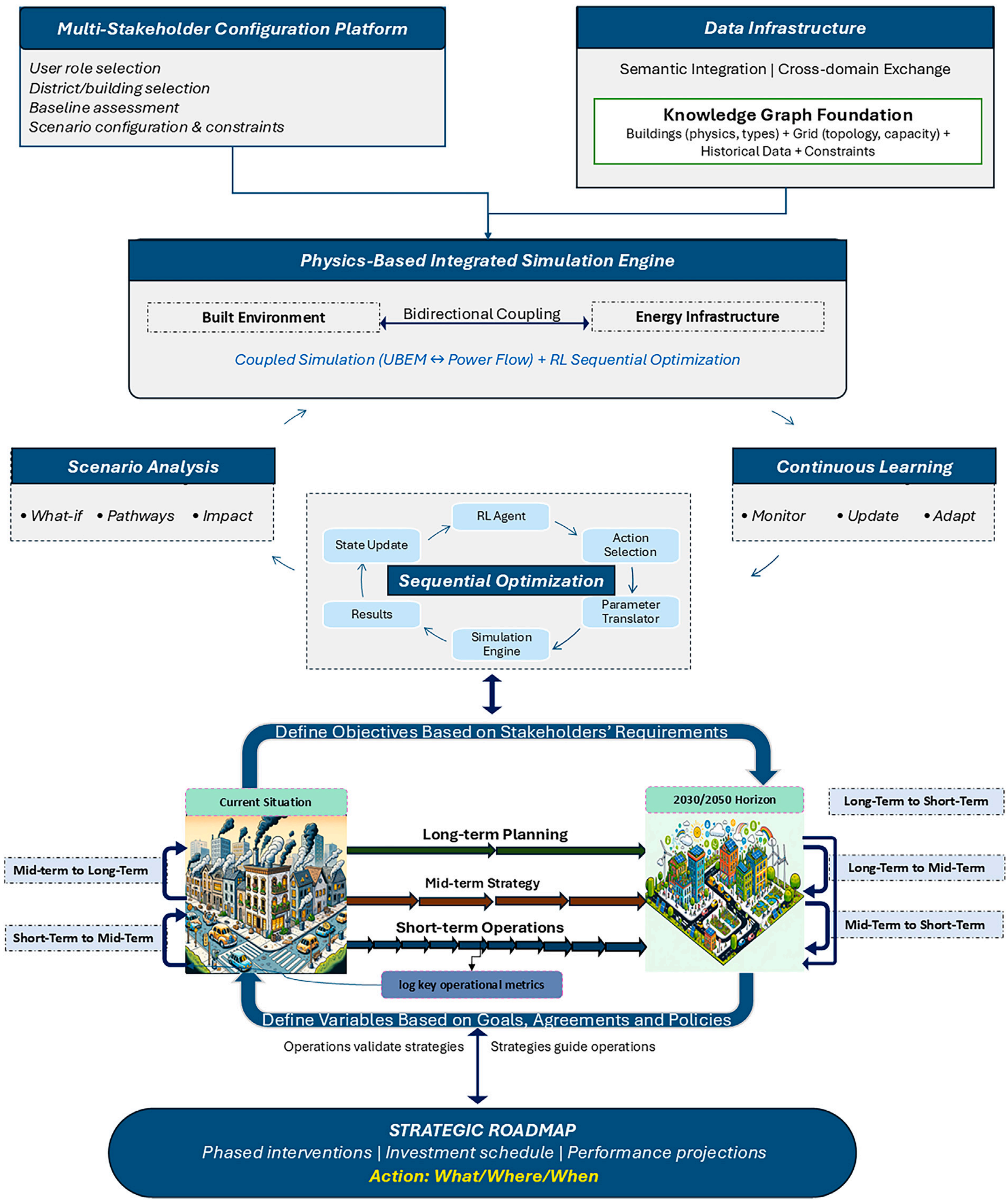


Fig. 9. Proposed integrated DT framework for district energy planning.

achieving decarbonization goals under uncertainty. The resulting pathway specifies *where* (which buildings/feeders), *when* (intervention timing), and *what* (technology combinations) to implement, with accumulated rewards tracking progress toward economic (net present value), environmental (emissions reductions), policy (renewable targets), building (comfort, efficiency), and grid (reliability, capacity) objectives across the planning horizon.

6.3. Mapping existing implementations to framework components

Table 4 maps existing implementations to framework components, showing what they demonstrate in semantic integration, coupled simulation, and sequential optimization, identifying missing capabilities, and proposing integrated district energy planning approaches. This systematic assessment reveals that while individual components exist in mature form within specialized domains, their integration for district-scale energy planning remains an open challenge.

Table 4
Framework component implementations: mapping existing research to integration requirements.

Framework component	Existing implementation(s)	What they demonstrate	What's missing	Framework contribution
Knowledge graph integration	Akroyd et al. [103], Zucconi et al., Bjørnskov & Jradi [42], Jahromi et al. [3]	Semantic data infrastructure linking domain standards (BIM/IFC, CIM, CityGML, SAREF). Geospatial queries connect building locations with grid topology.	Heterogeneous data formats across domains require manual integration. Spatial data infrastructure linking building geometry and grid topology lacks standardization.	Framework provides semantic infrastructure unifying heterogeneous data formats. Spatial data infrastructure supports integrated district energy transition.
Coupled simulation	Johari et al., Zhang et al. [20], Satchwell et al., Yang et al. [67]	Building energy models generate demand profiles validated against utility data. Power flow analysis identifies grid impacts from building interventions.	Critical automation gap: Manual coupling via custom scripts. Cannot scale to district-wide scenarios. One-way coupling without feedback loops.	Framework requires automated coupling infrastructure with standardized interfaces. Cloud-based parallel execution. Bidirectional feedback where grid violations trigger building refinement.
Sequential optimization	Pang et al., Yuan [95], Gao et al. [101], Shen et al. [137]	Deep RL for long-term strategic planning. Multi-objective optimization balancing economic, resilience, and environmental goals.	Building retrofit sequencing absent. Path effects not captured. Domain isolation: building and grid optimization proceed independently.	Framework needs unified optimization across domains with joint action spaces for building retrofits AND grid investments. Scenario-based robust optimization.

6.4. Strengthening domain connections through semantic integration

6.4.1. Coordination need

As documented in Sections 4.1 and 5.5.1, building and grid domains employ fundamentally different conceptual models, creating semantic fragmentation that prevents coordinated analysis without formal bidirectional translation mechanisms.

6.4.2. Framework response: knowledge graph architecture

Knowledge graphs provide infrastructure unifying disparate data sources while preserving domain semantics. Building on semantic standards reviewed in Section 5.5.3 (CIM for grid components, BIM/IFC for buildings, SAREF for cross-domain bridges) and implementations like the World Avatar project (Section 5.5.1), the framework adds district energy planning concepts: load aggregation patterns, hosting capacity constraints, and intervention sequencing dependencies. Spatial integration through GIS and CIM enables queries spanning building characteristics through distribution networks to substation constraints. This enables cross-domain analyses. The framework implements bidirectional translation layers where building characteristics (thermal mass, equipment schedules) map to grid-relevant parameters (demand flexibility, ramp rates), while grid constraints (voltage bands, protection settings) translate to building operational boundaries. Cross-domain queries—"which buildings could defer a transformer upgrade?" or "which buildings could provide evening peak reduction?"—become answerable by linking thermal storage capacity with load forecasts while preserving existing domain models.

6.5. Strengthening temporal coordination across planning horizons

6.5.1. Coordination need

Despite parallel temporal structures across building and grid systems (Section 5.5.2), operational insights remain disconnected from strategic planning. Grid planning employs static building assumptions while monitoring data rarely informs infrastructure decisions, and current approaches handle timescales independently despite coordination opportunities.

6.5.2. Framework response: coupled simulation engine

District energy analysis currently employs Urban Building Energy Models (UBEM) and power flow tools as separate workflows. The framework creates tightly coupled pipelines where UBEM-generated profiles immediately feed power flow calculations, revealing how district interventions stress feeders or create reverse power flows. Bidirectional coupling enables feedback: grid constraint violations inform building intervention refinement, creating iterative convergence on feasible strategies. Temporal coordination extends beyond coupling model types to linking timescales through multi-fidelity approaches: high-resolution operational models inform strategic planning parameters, real-time monitoring calibrates building models for improved long-term projections, and seasonal analyses reveal intervention performance across weather patterns. This addresses how building retrofits affect peak loads immediately, influence grid investments over years, and shape district profiles for decades—treating building-grid systems as co-evolving entities where interventions reshape future decision landscapes.

6.6. Enabling sequential planning through optimization

6.6.1. Coordination need

Current optimization evaluates interventions independently, missing sequential dependencies where order fundamentally shapes outcomes: envelope retrofits reduce loads, enabling smaller heat pumps and greater solar hosting capacity, while early battery placement improves subsequent renewable integration economics.

6.6.2. Framework response: sequential optimization component

The framework employs RL to learn optimal intervention sequences. While RL demonstrates operational success—battery scheduling, demand response—the framework extends these to strategic planning where order determines outcomes. Hua et al. [140] demonstrate progress in bridging timescales through DT-based RL for network reconfiguration, achieving cost reductions. State representations capture building characteristics, grid topology, installed technologies, and costs. Actions include envelope retrofits, HVAC replacements, solar, batteries, and grid upgrades. Reward functions balance emissions, costs, reliability, and stakeholder preferences. Through simulated exploration of district futures, agents learn which sequences achieve goals effectively. This reveals non-obvious strategies: prioritizing commercial retrofits in district cores for transformer loading benefits, concentrating storage at specific nodes to enable broader solar adoption, or small-scale pilots providing operational data reducing uncertainty for large-scale rollouts. Extending RL to strategic timescales requires addressing uncertainty over decades, technology evolution, and multiple objectives. The framework employs scenario-based RL where agents learn robust strategies across multiple futures rather than optimizing for single conditions.

6.7. Cross-cutting infrastructure: stakeholder coordination platform

District energy transitions involve diverse stakeholders: grid operators prioritizing reliability, urban planners seeking sustainability, building owners focusing on returns, and policymakers pursuing emission targets. Current tools struggle to reconcile these trade-offs—grid-focused tools optimize stability without building economics, while building models ignore grid constraints. The platform translates optimization into stakeholder insights: infrastructure deferral (operators), intervention sequences (planners), savings projections (owners), and emission impacts (policymakers). This enables participatory scenario analysis where stakeholders adjust parameters, explore alternatives, and understand trade-offs. Evolving regulatory frameworks increasingly enable models where infrastructure budgets can fund customer-side efficiency improvements. The platform quantifies benefits across groups: utilities defer capital, building owners receive incentives, and communities achieve targets. Network analysis (Section 4.1) revealed that technical separation reflects institutional barriers. The platform addresses this by creating spaces where groups develop shared language, catalyzing integration-focused communities fluent in multiple domains.

6.8. Managing uncertainty

Strategic planning confronts uncertainties in demand growth, renewable variability, technology costs, policy changes, and climate impacts compounding over decades. Three categories prove particularly relevant: (1) data uncertainties from sensor accuracy and archetype assumptions, (2) model uncertainties from simplified physics representations, (3) behavioral uncertainties in occupant patterns and adoption rates. These uncertainties interact and amplify across domain boundaries. Building variabilities aggregate non-linearly at district scale while grid constraints impose hard limits. The framework employs probabilistic approaches capturing full outcome distributions—expected impacts plus confidence bounds and risk profiles. This proves valuable when uncertainties cascade through intervention sequences, showing stakeholders not only expected impacts but ranges under different scenarios. Scenario-based methods enable agents to learn robust strategies through exposure to diverse futures during training. Rather than assuming perfect foresight, sequential optimization experiences uncertainty during learning, developing strategies hedging against unfavorable outcomes while capitalizing on opportunities. This aligns with decision-making under deep uncertainty, acknowledging adaptive strategies succeeding across plausible ranges prove more useful than single-future predictions.

7. Discussion

The pronounced fragmentation revealed through network analysis has profound implications for district energy planning. Low cross-domain connectivity despite critical interdependencies suggests that coordination difficulties stem not from technical impossibilities but from misaligned incentives, incompatible methodologies, and separate institutional structures. Researchers optimize within familiar domains rather than bridging unfamiliar territories.

The framework's significance lies in understanding each domain's objectives, constraints, solutions, and stakeholder motivations, then enabling them to work together through integrated infrastructure. This advances DT maturity from simple monitoring or what-if scenario tools toward recommendation systems capable of strategic guidance. Recognizing district transformation as sequential planning rather than static optimization—whether linear or nonlinear—proves essential: decisions create path dependencies where early interventions reshape subsequent possibilities, requiring RL approaches that discover effective sequences through simulated experience. Prior district energy approaches assumed data platforms or semantic standards would suffice for integration. Our analysis demonstrates otherwise—coordination requires simultaneous advances across semantic translation mechanisms, temporal coupling infrastructure, and organizational alignment structures.

Implementation confronts interconnected challenges amplified by uncertainty. Computationally, district-scale coupled simulation demands substantial resources while propagating uncertainties across model boundaries. As strategic planning horizons extend and components integrate, uncertainties and probabilities compound: building retrofit performance varies with occupant behavior, renewable generation fluctuates with weather patterns, technology costs evolve unpredictably, and policy frameworks shift across decades. These cascading uncertainties, absent in operational optimization, demand probabilistic approaches and scenario-based methods. Organizationally, utilities operate under cost-recovery regulation incentivizing capital investment while building efficiency programs require rapid paybacks. Economically, coordination benefits accrue across stakeholder groups over decades while costs concentrate upfront.

7.1. Limitations

This review primarily examined electrical systems, giving limited attention to heating/cooling networks increasingly relevant for district energy. The search strategy focused on “DT” terminology, possibly missing relevant integration work using different frameworks. Most critically, the proposed framework awaits empirical validation—while individual components find literature support, integrated implementation in real districts remains unexplored.

7.2. Future directions

Several research directions emerge. Pilot implementations in instrumented districts could validate framework components and reveal integration challenges. Development of standardized interfaces enabling tool interoperability without wholesale replacement represents critical enabling infrastructure. Economic assessment methodologies quantifying distributed benefits across stakeholders would support business model development.

District energy transformation requires moving beyond infrastructure expansion for worst-case scenarios toward adaptive frameworks leveraging operational data and coordinated optimization. The path forward builds on domain strengths while creating integration mechanisms that enable buildings and grids to inform each other's evolution.

8. Conclusion

Current district energy planning approaches fragment what must be unified: building improvements proceed independently from grid evolution despite their fundamental interdependence. This systematic review of 139 DT implementations reveals why promised integration remains elusive—not from technical impossibility but from research communities, professional structures, and institutional incentives that resist coordination.

The proposed framework demonstrates how integration becomes actionable: not by replacing existing domain expertise but by creating infrastructure that enables specialists to understand consequences beyond their boundaries. This represents a conceptual shift—from treating buildings and grids as separate systems requiring connection, to recognizing districts as inherently coupled systems requiring decomposition for practical management then reintegration for strategic planning. DTs evolve from documentation and monitoring technologies into platforms where distributed decisions inform each other across organizational boundaries and temporal scales.

Transforming districts to meet climate targets demands this integrated perspective. Cities cannot afford parallel efforts where building retrofits proceed without considering grid impacts, or grid expansions occur without leveraging building flexibility. The technical capabilities exist across specialized domains. What remains absent are the institutional structures, standardized protocols, and aligned incentives enabling coordination. Progress requires action from multiple actors:

researchers demonstrating integration value through pilots, standards bodies enabling interoperability, and policymakers restructuring incentives. Success belongs to communities recognizing that district transformation is not a technical problem requiring better tools, but a coordination problem requiring institutional innovation.

CRediT authorship contribution statement

Amin Jalilzadeh: Conceptualization, Investigation, Writing – original draft, review & editing. **Azarakhsh Rafiee:** Supervision and Review. **Peter van Oosterom:** Supervision and Review. **Thaleia Konstantinou:** Supervision and Review.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Claude AI in order to improve grammar, enhance readability, and polish draft texts. The AI was used as a language enhancement tool to improve the clarity and flow of the manuscript. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

No data was used for the research described in the article.

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