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Energy retrofits for smart and connected communities: Scopes and technologies

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ABSTRACT

The trajectory of sustainable urban development evolves with the integration of intelligent technologies, extending beyond individual buildings to encompass entire communities interwoven with smart systems. Energy retrofits at smart and connected communities are crucial for sustainable urban renewal, yet they present distinct challenges from individual home retrofitting. However, a comprehensive understanding of the emerging research scopes and technologies in large-scale energy retrofits is lacking. To address this problem, this research systematically reviews journal publications in this field from 2000 to 2023. Results disclose four research scopes: building construction, mechanical systems and equipment, electrical systems and computing, and human-centered design and connectivity, suggesting a new landscape for energy retrofit research, which largely extends beyond the traditional field of the built environment (e.g., heating, cooling, lighting, and structure) to advanced computing, renewable energy, and human-centered connectivity. Results also delineate a new paradigm of retrofit technologies with three focused areas: within-building optimizations (heating and air conditioning, envelope, engineering design, and smart technology), between-building connections (power grid, district energy, and integrated energy system), and whole-community integrations. They represent the nodes, ties, and interplay within community networks. Eight retrofit focuses and their specific technologies and computational techniques are summarized and examined. Notably, the approach of simulation and computational modeling is prevalent, with evolutionary algorithms featured in computational techniques. The review suggests five gaps and proposes a roadmap to advance future research in energy retrofits, specifically emphasizing the integration of intelligent technologies and multidisciplinary collaborations.

1. Introduction

Large-scale building energy retrofits play a crucial role in promoting sustainable urban renewal. The retrofit implementations yield substantial energy savings to existing buildings where people spend 90 % of their lifetime. Given the fact that buildings consume 40 % of the global energy [1], large-scale building energy retrofits demonstrate the potential to reduce 60–80 % of the consumption and 30 % of CO_2 emissions [2]. This is important for developed regions, for example, North America where over 44 % of existing buildings would be renovated or replaced [3]. With the projected global urban population reaching 6.7 billion by 2050, the associated escalation in energy demand, estimated between 45 and 59 quintillion joules in the coming decades, underscores the urgency of large-scale energy retrofits. Notably, residential building retrofits demonstrate greater potential for energy savings [4]. The implementation of these retrofits at the community level is imperative to curbing energy consumption and enhancing the quality of life for billions of urban residents [5].

Large-scale building energy retrofits also generate societal impacts through two avenues. First, the adoption of green building technologies noteworthily reduces energy expenditure and makes housing more affordable, especially for the low-income. For example, 138 million US households allocate 8–14 % of income on energy costs [6]. Second, the economic ramifications of large-scale retrofits are evident in cities grappling with economic decline and widespread abandonment of residential, commercial, and industrial structures. For example, the city of Detroit exemplifies this issue with thousands of abandoned houses, causing social degradation and posing threats to public health and community well-being.

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Abbreviations

ABM	Agent-based modeling
ANN	Artificial neural network
EA	Evolutionary algorithm
EV	Electric vehicle
GA	Genetic algorithm
GIS	Geographic information system
HVAC	Heating, ventilation, and air conditioning
IOT	Internet of things
MPC	Model predictive control
NSGA-II	Non-dominated sorting genetic algorithm II
PCM	Phase change material
PSO	Particle swarm optimization
PV	Photovoltaics
RL	Reinforcement learning
S&CC	Smart and connected communities

The shift of cities towards a high-energy-efficiency and low-carbon scenario, as exemplified in the green building movement [7], holds the potential to advance large-scale building energy retrofits. However, challenges persist in the domain of scopes and technologies for energy retrofits in interconnected communities. These challenges encompass the intricate interplay between the effects of building technologies and occupant behaviors [8], the identification of factors for optimal building retrofit solutions [9], and the interactions among buildings [10]. Nevertheless, the emergence of intelligent technologies offers a technical solution to address this complexity, providing the possibility to realize the optimal energy retrofits in the future communities – the smart and connected communities (S&CC). An S&CC is delineated as a community seamlessly integrating intelligent technologies with natural and built environments. The expansion of S&CC is apparent and its importance is emphasized as more US communities enter a transformative era marked by the integration of residents and their surroundings through dynamic intelligent technologies.

Overall, emerging S&CC demonstrate significant promise for extensive energy retrofits and increased energy savings in the future. However, compared to retrofitting individual buildings, the community-level retrofitting presents more challenges and uncertainties that remain unexplored in the current literature. Krarti [11] reviewed the building codes and evaluated the economic and environmental benefits on the retrofitted buildings after adopting the codes. Pérez-Lombard et al. [12] reviewed the information of building systems that required to improve energy retrofit. Shu and Zhao [13] reviewed decision making approaches to optimal retrofits for single buildings. Li and Wen [14] reviewed the technologies of mechanical systems for building control and operations. Yet, these reviews only concentrate on specifical aspects of retrofit technologies, mostly at the individual building level, overlooking connections between buildings and neglecting the rise of intelligent applications in buildings. This research distinguishes itself from prior reviews by aiming to delineate the future landscape of energy retrofits in S&CC, particularly outlining new research scopes and retrofit technologies. Unlike reviews addressing only fragments of the puzzle, this study provides a comprehensive overview essential for architects, engineers, and builders to comprehend the broader picture of future community energy retrofits. By doing so, it sets the stage for researchers in the domain of buildings (e.g., architecture/civil engineering), anticipating the integration of more smart applications and advanced computing into this traditional field, spanning from single buildings to the broader context of smart and connected communities.

2. Methods

Fig. 1 illustrates the methodological workflow for this research [15]. The procedure started with clusters of synonyms for keywords to identify topics of smart energy retrofit technologies at the community level. Three clusters of synonymous keywords and one additional single word were used in the search: (1) keywords of “retrofit”, “renovate”, “refurbish”, “transition”, “shift”, and “optimize” were used as alternatives to address the energy retrofit endeavor; (2) keywords of “community”, “neighborhood”, “district”, “urban”, “regional”, and “city” were used to define the scope of energy retrofit efforts at a large scale; (3) keywords of “smart”, “AI”, “intelligent”, and “artificial intelligence” were used to target the most advanced intelligent solutions; and (4) the word “energy” was used to focus energy performance of the technologies. Then, a systematic search was performed on major literature databases such as Web of Science and Scopus, with a focus on peer-reviewed journal articles published between 2000 and 2023. A total of 1149 articles were identified in the Web of Science database and 1081 articles yielded in Scopus. The research removed 668 duplicates, 892 noneligible articles, three irretrievable articles, 75 nontechnical reports, 131 macro-policy analyses, and 260 infrastructure studies. Overall, the comprehensive review includes 201 peer-reviewed journal articles distributed from 81 journals.

The analysis approach includes bibliometric reviews and descriptive statistical analyses on journal outlets, publication date, author affiliation, geographical distribution, expertise area, and key technological terms. Detailed technological specifications and applications evaluations are summarized. Technological and methodological gaps are discussed, and future research roadmaps are suggested.

3. Bibliometric results

Fig. 2 shows the number of per-year publications from January 2011 to October 2023. Although the start year in this literature search is 2000, publications emerge in year 2011. The number of articles published per year continuously increases after 2014, suggesting more studies involved in the concerted efforts as inspired by impending global initiatives such as the Paris Climate Agreement in 2015 and the UN’s Sustainable Development Goals (SDGs) in 2016. Additionally, the drop of 2023 in the chart does not indicate a decrease of publications but reflects on the data collection of this study ended in October 2023.

Fig. 3 displays the affiliation distribution of the authors who are from 53 countries or regions. Especially, the largest portions include China (11.4 %), Italy (10.8 %), and the US (9.2 %), followed by India (4.9 %), the UK (4.6 %), Pakistan and Spain (equally 3.3 %), and Canada (2.9 %). The eight countries totally own half of the contributors around the world. These countries often have a large number of historical buildings or large populations, which demands a greater focus on large-scale energy retrofit. Geographically, most of the studies come from Europe (22 countries, 43.8 %) and Asia (16 countries, 31.7 %), followed by America (6 countries, 16.0 %), Africa (7 countries, 5.6 %), and Oceania (2 countries, 2.6 %).

Fig. 4 shows six expertise areas among the authors, indicating a multidisciplinary nature of research in large-scale energy retrofits. The top expertise areas, listed in a descending order of their representation, are as follows: electrical engineering and computer science (26.8 %), energy and environmental engineering (22.6 %), architecture, construction, and civil engineering (17.6 %), industry and industrial engineering (13.1 %), mechanical engineering (10.5 %), and sociology and economics (9.4 %). It is noteworthy that the collective expertise of architectural, civil, mechanical, and construction engineering accounts for only 28.1 % of the overall expertise area, even though these areas represent the traditional disciplines pertinent to building energy retrofit.

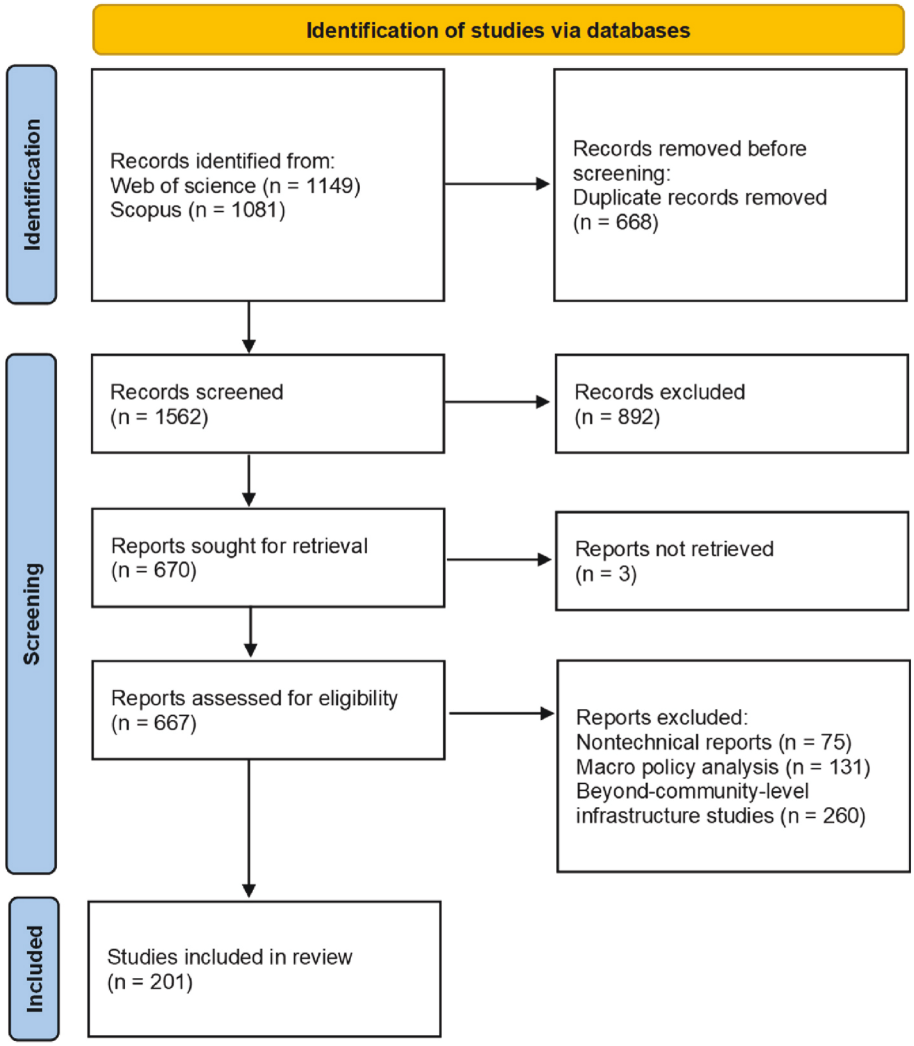

Fig. 1. Flow diagram of literature screening process.

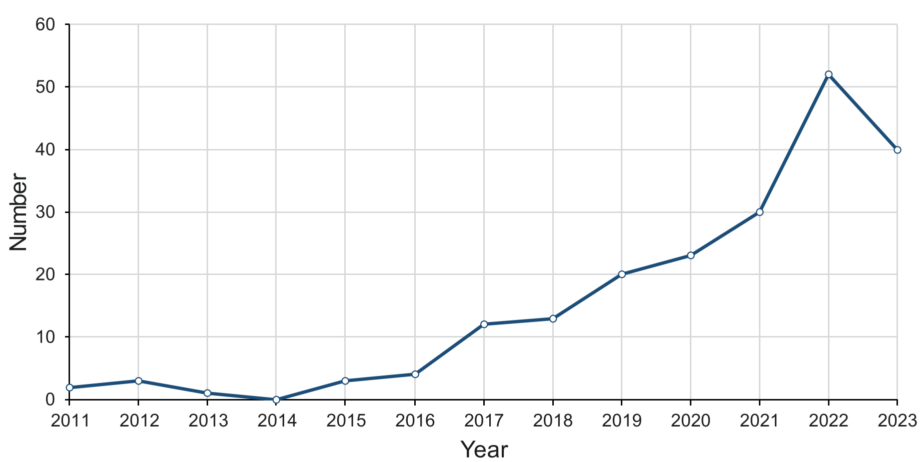

Fig. 2. Number of publications by year.

4. Results: A landscape of research scopes

Fig. 5 visually exhibits four research scopes and their interactions through terms mining network analysis, unveiling an extended landscape beyond the traditional built environments. In the network diagram, the size of circles represents the occurrence frequency of each term; the distance between circles represents the co-occurrence probability; the thickness of lines represents the connection strength between terms; and the color denotes term clusters that share a relevant topic. Overall, the results confirm an existing scope (i.e., building construction) and identify three new scopes (i.e., "electrical systems and computing," "mechanical systems and equipment," and "human-

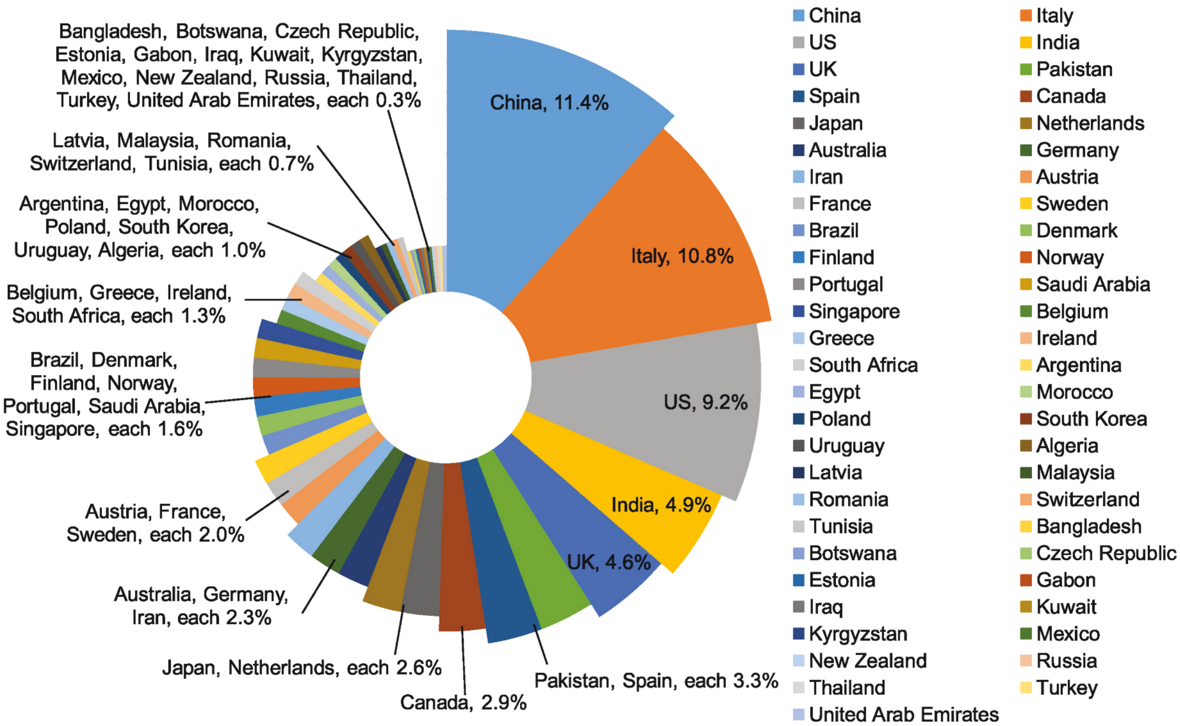

Fig. 3. Distribution of research by the country of affiliation (Round-off error may occur).

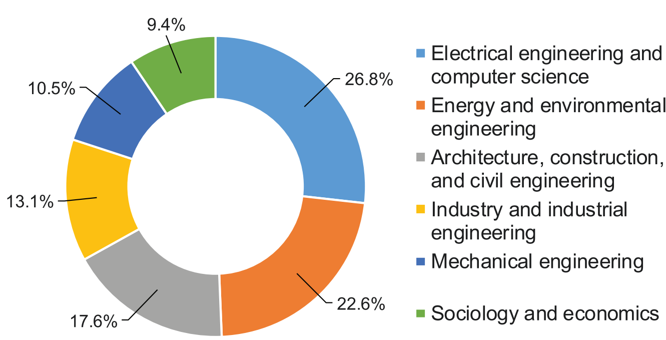

Fig. 4. Distribution of research by author expertise area.

centered design and connectivity”).

The first research scope delineates the traditional domain of building construction for energy retrofit research (green). At the core of this scope lies the term “building”, suggesting the enduring significance of buildings in energy retrofit research. Other key terms in this cluster include “energy efficiency”, “energy saving”, “heating”, “control strategy”, “energy storage”, “temperature”, “parameter”, “window”, “climate”, “occupant”, “thermal comfort”, “MPC” (model predictive control), and “PCM” (phase change material). These terms emphasize several critical research subareas closely linked to the field of building construction. They include: the exploration of energy storage solutions (e.g., leveraging PCM for building thermal storage, and employing battery technologies to harness surplus solar energy), the optimization of building energy control strategy (e.g., MPC) to heighten energy efficiency, the optimization of building parameters and heating temperature control to enhance energy savings and occupant comfort, and the evaluation of the smart building components (e.g., window) in different climates. Noteworthily, strong ties in this research scope include “building-comfort” and “building-energy efficiency”, indicating that the concentration of this research scope remains primarily focused on enhancing energy efficiency while ensuring the comfort of the occupants. New ties are identified, for example, “building-energy storage,” and they imply new research subareas in the future.

The second research scope represents the domain of electrical systems and computing (red). The pivotal terms in this scope are “algorithm”, “grid”, and “community”. Rather than traditional electrical components in buildings (e.g., lighting), these terms highlight a significant emphasis on intelligent optimization and computational techniques of power grids on a community scale. The terms comprising “peer”, “prosumer”, “customer”, “user” “energy community” and “DER (distributed energy resource)” collectively reflect an increasing interest in distributed energy sources for sustainable community development. The terms encompassing “uncertainty”, “architecture”, “electricity bill”, “electricity cost”, “electricity consumption”, “peak hour”, and “peak load”, signify that the primary objectives of power grid optimization revolve around these factors. Other terms include “electric vehicle” (EV), “appliance”, “energy management”, “demand response”, “demand side management”, “smart grid”, and “smart home.” They emphasize new research subareas closely linked to the field of smart grids such as vehicle-to-home framework, demand side management of smart home, demand response, peer-to-peer energy sharing and trading. Notably, the strong tie within this scope is “community-algorithm”, underscoring the growing and critical role of advanced computing in community-scale energy retrofit.

The third research scope represents the domain of mechanical systems and equipment (blue). At the heart of this scope is the fundamental term “network”, signaling a longstanding focus on energy system network. The terms encompassing “RES” (renewable energy system), “REC” (renewable energy certificate), “renewable energy source”, “supply”, “flexibility”, and “transition” underscore the significance of renewable energy integration on the sustainable transition and the flexibility of energy supply. The terms including “vehicle”, “heat pump”, “controller”, “heat”, “district heating”, and “microgrid” collectively reflect growing attention towards utilizing vehicles, heat pumps, and controllers to optimize district heating and microgrid operations. Other terms like “neighborhood”, “district”, “cluster”, “country”, and “planning” show large and diverse scales of research on energy systems.

The fourth research scope delineates an emerging domain of human-centered design and connectivity (yellow). Key terms in this scope

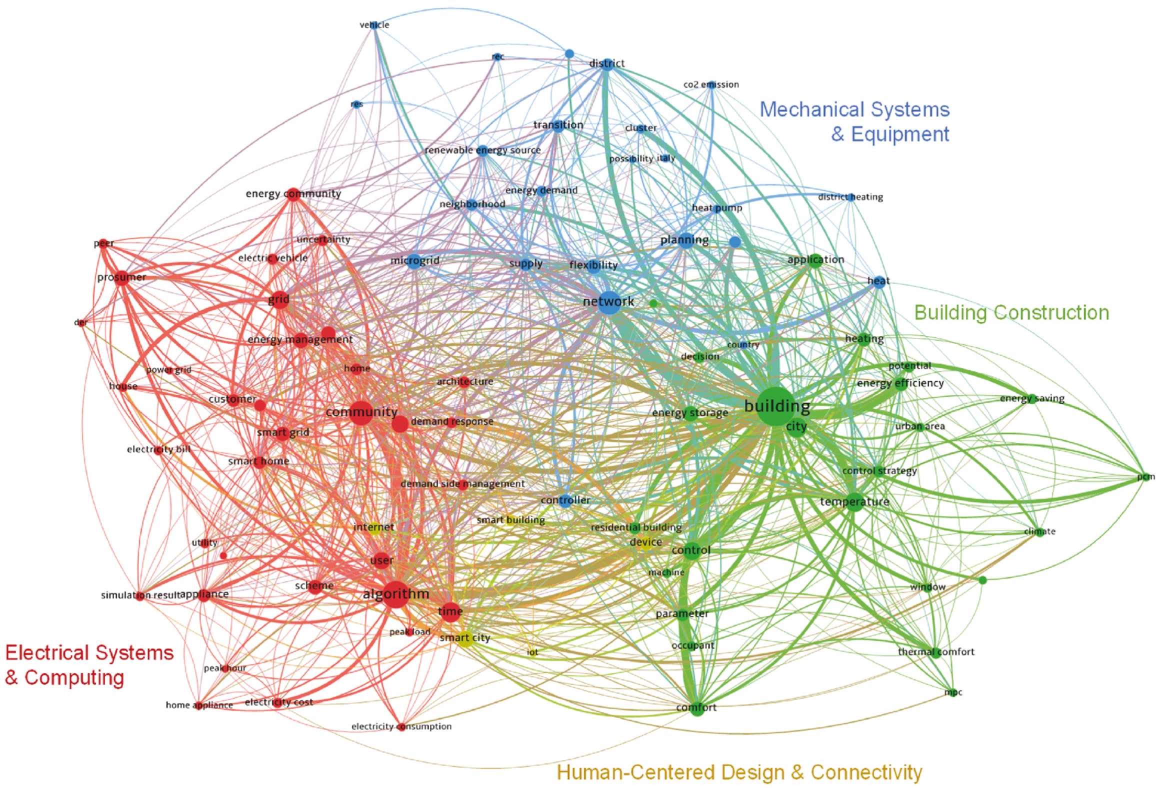

Fig. 5. Network diagram of research scopes.

include "internet", "IoT (internet of things)", "smart city", "smart building", and "device". These terms signify the primary focus on the integration of advanced digital technologies and interconnected devices to amplify human needs and enhance urban energy efficiency.

In summary, the four research scopes demonstrate a new landscape for energy retrofit research, which largely extends from the built

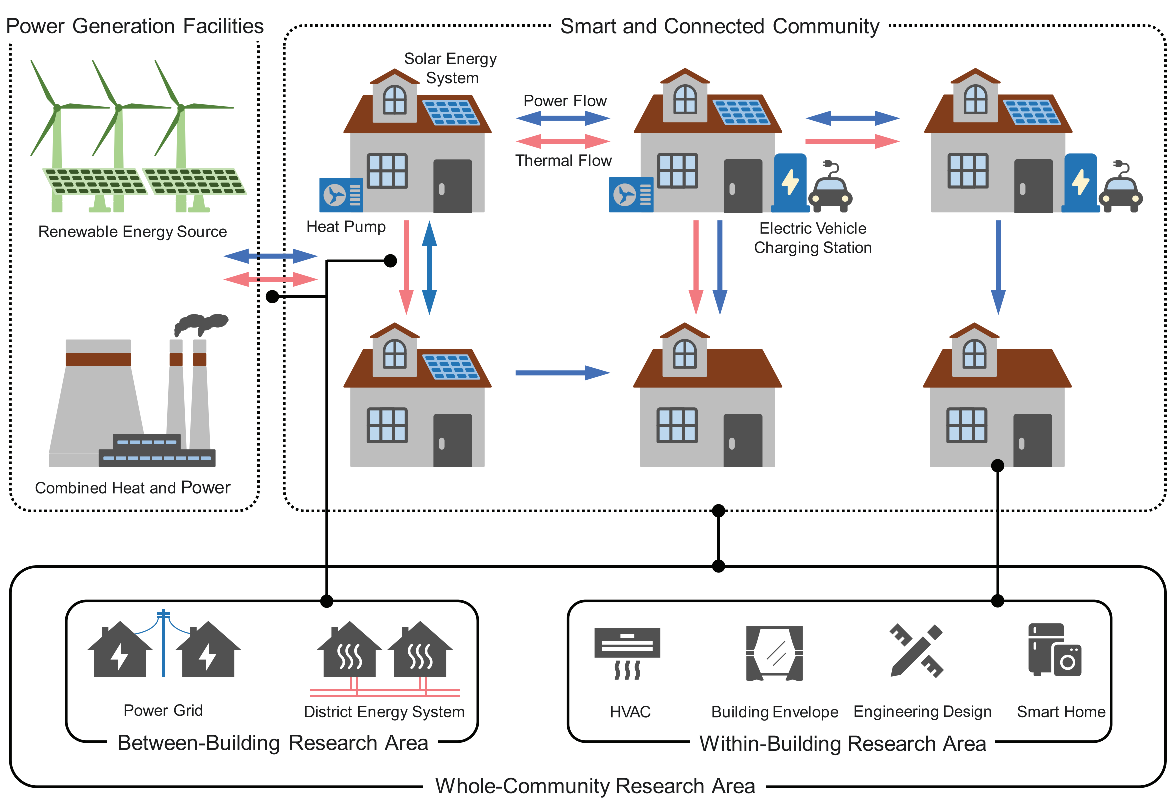

Fig. 6. The paradigm of energy retrofit technologies at the community level.

environment (heating, ventilation, and air conditioning (HVAC), lighting, structure, etc.) to advanced computing, renewable energy, and human-centered connectivity. Nonetheless, notable strong ties bridge different research scopes such as "building-network" and "building-algorithm". The cross-scope ties suggest a considerable portion of research in the application of intelligent optimization algorithms, and the expansion of individual building research to encompass larger scales by analyzing networks of building. Overall, these interconnected scopes emphasize a multidisciplinary nature of research in this area and enhance the necessity of collaboration drawing on a synergy of expertise to address the complex challenges associated with large-scale energy retrofit.

5. Results: A paradigm of retrofit technologies

5.1. Overview

Fig. 6 displays the paradigm of retrofit technologies in S&CC networks made of nodes and ties. Based on the network theory, each building denotes a node, and each connection denotes a tie [16]. For example, house A and house B are connected by the same utility company – house A and B are two nodes and the electricity grid is the tie. Of course, the two houses (two nodes) can be connected by other ties such as heat pipes. The paradigm includes three focused areas of energy retrofit technologies. (1) The first area refers to the energy retrofit technologies within buildings, including HVAC, building envelope, engineering design, and smart home systems. (2) The second area refers to the energy retrofit technologies between buildings, typically power grid and district energy system, including the optimization of energy

Table 1
Summary of energy retrofit technologies of reviewed publications.

Area	Focus	Technology	Description	Computational Technique	Reference
Within-Building Optimization: The nodes of S&CC networks.	HVAC	MPC	An advanced control strategy that uses a predictive model to estimate and control future system behaviors. It optimizes HVAC control actions over a time frame and adheres to system constraints.	Energy simulation, tree-based methods, EA	[17,18]
		Energy performance assessment	Comprehensive data analysis and energy simulation approaches to assess HVAC systems and then recommend solutions for improvement.	Energy simulation	[19,20]
	Building envelope	Renewable energy integration	Installation of solar panels on building envelope spanning a range of applications from small-scale façade modules to large-scale structures.	Energy simulation, tree-based methods, neural network model, EA	[24,26,30–32]
		Advanced materials	Innovative materials applied in building envelopes, e. g., PCM and thermochromic materials.	Energy simulation	[36,42]
	Engineering design	Production design optimization	Architectural design options or occupant-involved simulations to model and optimize energy performance.	Energy simulation, ABM, tree-based methods, EA	[44,45,51]
		Multi-solution decision-making	Decision-making models, approaches, and solutions to enable optimal building energy retrofits.	Energy simulation, neural network model, EA, GIS, PSO	[52,55,58,63,65,68]
	Smart home	Smart operations & management	The energy management of connected appliances and building systems to enable remote control or autonomous operations through user scheduling or sensing.	Energy simulation, neural network model, EA, IoT, VPP	[70–72,74,75,77,82,84,85,87,89,91]
		Distributed energy management	Hardware and software to enable connections and control of smaller energy generation and storage units on the consumer's side, e.g., solar panels, batteries, and other edge devices.	Energy simulation, IoT, neural network model, RL	[62,94,99]
Between-Building Connections: The ties of S&CC networks.	Power grid	Demand response	Building energy consumption response strategies to adjust electricity demands in response to grid conditions, e.g., peak demand period.	Energy simulation, neural network model, EA, IoT, PSO	[106,108,109,115,116]
		Energy sharing and trading	Technics and strategies for sharing and trading electricity supply to distribute or exchange energy among buildings.	Energy simulation, block-chain, GIS, IoT, multi-agent system, EA, RL, VPP	[31,121,122,126,128,129,131]
		Microgrid energy management	Optimization techniques in the context of managing building energy consumption demand and supply in community settings.	Energy simulation, neural network model, IoT, EA, PSO	[141,143,144,148,149,153]
	District energy system	Demand response	Strategies for adjusting building energy consumption in response to district heating and cooling conditions, such as peak demand periods, to manage district energy system load.	Energy simulation, neural network model, EA	[158,162]
		Energy sharing and trading	Technics and strategies for the sharing and trading thermal energy to distribute or exchange energy among buildings.	Energy simulation, EA	[163]
		Energy performance assessment	Assessment of the effectiveness of different district energy system operation strategies	Energy simulation, digital twin	[165,166]
	Integrated energy system	System optimization	Strategies and optimization techniques to improve the energy efficiency of integrated energy systems.	Energy simulation, block-chain	[170,173,178,182,183]
		Energy interaction analysis	Analysis of the interplay between various energy systems, especially electricity and thermal energy.	Energy simulation	[184,186,191]
Whole-Community Integrations: Nodes and ties of S&CC networks.		Large-scale building and energy system modeling	Investigations of both building retrofitting and optimizing energy systems connected to building stocks	Energy simulation	[194,195]

Notes: HVAC=Heating, Ventilation, and Air Conditioning, MPC= Model Predictive Control, PCM=Phase Change Materials, EA = Evolutionary Algorithm, GIS= Geographic Information System, ABM = Agent-based Model, PSO= Particle Swarm Optimization, IoT = Internet of Things, RL = Reinforcement Learning, VPP=Virtual Power Plant.

distribution between energy stations and the community, as well as the optimized distribution of energy among various buildings within a community. (3) The third area refers to the energy retrofit technologies in an integrated community of both buildings and their connections of electric and thermal energy. Interestingly, from a network perspective, the first area denotes the nodes of a S&CC network, the second area delineates the ties of a S&CC network, and the third area covers a whole S&CC network including both nodes and ties.

This study is interested in the research methodologies applied in studies focusing on the design, development, or evaluation of energy retrofit technologies. The classification of these studies reveal the following distribution of methodologies: 83 % employ simulation and computational modeling, such as using software like EnergyPlus or TRNSYS for energy performance prediction; 7 % estimate the expected impacts of actual retrofit projects through various evaluation tools and data analysis techniques, such as cost-benefit analysis and lifecycle assessment; 7 % learn from retrospective reviews of projects to gather insights and experiences; and the remaining 3 % utilize experimental approaches, such as physical tests on building materials.

Notably, computational techniques showcase distinct prominence in current research approach. Evolutionary algorithms (EAs), encompassing methods like genetic algorithms (GAs) and non-dominated sorting genetic algorithm II (NSGA-II), dominate with a 13.4 % share in 201 publications. Linear and Nonlinear Programming methods, exemplified by mixed-integer linear programming (MILP) and mixed-integer nonlinear programming, represent 9.0 % of the techniques. Swarm intelligence techniques, which include particle swarm optimization (PSO) and ant colony optimization, make up 8.0 %. Neural network models, such as artificial neural networks (ANNs) and recurrent neural networks (RNNs), comprise 7.5 %. Game-theoretic optimization, emphasizing strategic decision-making exemplified by Nash equilibriums, holds a 3.5 % stake. Tree-based methods, spotlighting algorithms like decision trees and random forests, contribute 2.5 %. Reinforcement learning (RL), an approach where agents learn by interacting with their environment, as illustrated by Q-learning and deep Q networks, also accounts for 2.5 % of the techniques.

Table 1 summarizes the research focus, technology, and computational techniques for each of the three focused areas of retrofit technologies identified by the paradigm. The detailed retrofit technologies are explained, compared, and analyzed in the following sections.

5.2. *Focused Area#1: within-building optimizations – the nodes*

5.2.1. *High efficiency HVAC*

HVAC systems continue to play a crucial role in maintaining thermal comfort and indoor air quality during building energy retrofits. This research identifies two specific technologies from recent advancements in HVAC renovations.

The first is MPC, an advanced technology of process control. MPC employs a dynamic model to predict the future status of HVAC systems based on current control actions and measured outputs, such as temperature, humidity, and air quality. It utilizes these predictions to optimize future control actions to minimize energy costs and maintain acceptable indoor environment. Also, MPC leverages weather and occupancy predictions and holds the potential to enhance energy conservation, for example, by fine-tuning temperature settings and operation schedules. MPC outperforms the proportional-integral-derivative control in managing thermal comfort and efficiency, due to its rapid response, stability, minimal overshoot, and adaptability [17]. In addition, MPC plays a crucial role in load-shifting implementation and peak demand reduction, especially through combining precooling and thermal energy storage [18].

The second is system assessment and optimization, a process to refine existing HVAC system designs. This technology analyzes performance data, simulates energy consumption, and uses optimization techniques to reduce energy costs. For example, the data-driven approach of data envelopment analysis (DEA) can assess and pinpoint the optimal strategies for HVAC system enhancement [19]. Other simulation-based approaches are used to assess the potential of HVAC demand flexibility and renewable source integration [20], evaluate HVAC refurbishment scenarios [21], or design HVAC controls for chillers, compressors, and fresh air systems [22]. Notably, intelligent approaches such ANN-assisted optimizer and grey wolf algorithms are able to optimize the operations of HVAC systems [23].

5.2.2. *Building envelope*

Building envelopes are a fundamental component in determining energy consumption, serving as an interface between indoor and outdoor environments for heat and light transfers. This research identifies two specific technologies from recent advancements in envelopes.

The first refers to renewable energy integration with buildings. Solar facade modules [24] and building integrated photovoltaics (PV) [25] were developed to reduce heating and cooling loads and achieve net-zero energy use. Research in PV panel design maximizes annual solar radiation [26] and minimizes associated costs [27]. The PV design can scale up to urban environments to maximize solar energy harvesting, considering real-time electricity demand, architectural landscape preservation, and spatial constraints [28]. Other research in large-scale solar energy generation use methods and tools, including fast-evaluation with minimal computational resources [29], dynamic simulation-based evaluation [30], energy stress mitigation framework [31], comprehensive mapping with a quantitative visual impact assessment [32], and the home-developed TEAC software [33]. Outcomes of the research can produce PV solutions for a historic city [34]. Also notably, intelligent approaches such artificial bee colony algorithm are used to optimize PV systems, e.g., in estimating the life cycle cost [35].

The second refers to the advanced materials of various building components to improve energy efficiency. PCM in exterior facades can absorb and release thermal energy during their phase transformation [36]; PCM on interior surfaces can keep indoor thermal comfort without energy consumption [37]. Thermochromic materials – changing color based on ambient temperature – help reflect heat and mitigate overheating in summer, and absorb heat and enhance passive heating in winter [38]. Another innovation is shape-memory alloys that "remember" their initial shape and can return under certain conditions. The alloys enable self-reactive façade systems and modify building appearance adapting to environmental changes without external energy input [39]. Smart water-filled glasses, of which the internal water layer can absorb, store, and release heat, are used for smart windows to improve building thermal comfort [40]. Specific studies pertain to the smart windows examine vanadium dioxide (VO_2) coatings [41] and controllable absorbing layers [42].

5.2.3. *Engineering design*

The engineering design of buildings encompasses architectural design and building operation design. This research identifies two specific technologies from engineering design innovations.

The first refers to production design optimization. Architectural design process is optimized by surrogate modeling, an application of supervised machine learning that emulates the behavior of complex systems and facilitates a more streamlined, rapid, and efficient analytical process. The implications of surrogate modeling enable rapid and accurate predictions to optimize complex architectural parameters, such as daylighting performance of high-rise buildings [43], or thermal designs of building envelopes under budget constraints [44]. Another important approach is agent-based modeling (ABM), a computational method to simulate the actions and interactions of agents to assess their effects on building systems. ABM optimizes the complex interplay between energy consumption, indoor environment, and occupant behavior. Outcomes achieve sustainable building operations, e.g., a green campus with low energy use and high thermal comfort [45], or optimal energy performance against desired lighting, temperature, and air quality levels [46]. Notably, intelligent approaches are used in to improve thermal comfort, visual comfort, and energy consumption, for example, a tri-optimization for building shape and envelope properties [47], a NSGA–II–based multi-objective optimization for venetian blinds in office buildings [48], a simulation-based optimization for architectural design [49], hybrid machine learning algorithms to optimize heating and cooling loads in various climates [50], or the Bayesian multilevel additive modeling to optimize parameters in building typologies [51].

The second refers to multi-solution decision-making to determine the most effective building retrofit strategies. Energy simulation-based decision-making enables comparative analyses of energy use, CO_2 emissions, and cost decomposition to obtain optimal retrofit strategies [52, 53]. The energy simulator can be self-developed built on energy calculation standards [54]. Optimization modeling is another widely used decision making approach to energy efficiency retrofits [55]. This approach relies on mathematical models, for example, GA, computational fluid dynamics (CFD) [56], or the Taguchi method [57] to select the best solution from various retrofit scenarios in campus design [58], residential buildings [59], and urban environment [60]. Assessment-based decision making can yield user-centric energy retrofit solutions in a digital ecosystem [61], and address the problem of uncertainty through the use of fuzzy logic and Bayesian networks [62]. System-integration supports the decision making, for example, a GIS-embedded multicriteria spatial decision support system [63], or a web-based decision support system for the multi-energy planning of renewable energy in buildings and neighborhoods [64]. Additionally, the empirical approach (e.g., case studies and onsite observations) provides real project experience to improve the decision making in automatic controls and renewable energy, for example, in office buildings [65], library [66], residential buildings [67], or hotels [68].

5.2.4. Smart home

Smart home upgrading relies on advanced information technologies such as AI, IoT, renewable energy solutions, and energy storage. This research identifies two specific technologies.

The first refers to smart operations and management, which automatically and intelligently supervises energy loads and controls through AI and IoT devices. Smart operations enable demand response based on real time pricing, which adjusts electricity consumption in response to supply conditions [69], and coordinates appliances, power generation, grid support, and user comfort [70]. Home energy management optimizes controls to maximize energy use reduction [71]. IoT sensing can detect occupancy and based on which control electrical load [72]. The involvement of AI in energy management improves energy efficiency, prediction accuracy, and device operations [73]. Cognitive architecture uses IoT sensors and legacy systems learns from user behaviors to optimize building energy use during renovations [74]. A simplified method for automatically detecting anomalies in building energy consumption uses statistical pattern recognition and ANN to provide energy use feedback to occupants and guide them to adopt energy saving actions [75]. Home energy management can also apply to natural resource usage, and notify users of waste, and aggregate similar activities [76]. Overall, the technology of smart operations and management leverages occupant behavior to enable human-centered retrofit design and automation. Notably, a large amount of intelligent algorithms are developed in this technology, for example, the cloud-based appliance scheduling using ANN and GA [77], AI-based energy wastage and cost reductions using GA [78]. The multi-objective EA [79], fuzzy adaptive dynamic multi-objective algorithm [80], and greedy heuristic algorithm [81] are used to optimize deferrable appliances' schedule in households for energy saving and users satisfaction. The neural network Q-learning algorithm [82], bacterial foraging ant colony optimization algorithm [83], and NSGA-II [84] are used to reduce peak demand. The limited memory algorithm for bound constrained problems [85], binary orientation search algorithm [86], and game theory [87] are used to mitigate large-scale appliances energy demand. The extreme gradient boosting algorithm and long short-term memory (LSTM) algorithm are used to forecast hot water demand and optimize the electric water heater operation [88]. Large-scale virtual power plants (VPPs) enable load shifting [89] and novel controls lower district energy flow through charging of domestic hot water tanks [90]. In addition, evaluation approaches to smart energy management are developed to optimize investments [91] or compare working conditions in office buildings [92].

The second refers to distributed energy management, which facilitates localized energy production, storage, and distribution. Leveraging renewable resources like solar panels and energy storage systems, it fosters independent and efficient energy systems that cater to local demands while reducing dependency on conventional electric grids. An automatic power control and management system was proposed, which supplied power to home appliances based on the power demand [93]. Distributed energy management systems were presented to optimize renewable energy distribution and storage [94]. An optimization model was developed to determine optimal operation of home energy storage for energy saving and peak demand reduction [95]. A strategy minimizing total fuel consumption and extending batteries lifetime for offline smart homes was proposed [96]. One model was developed to optimize PV, batteries, and EV charging for minimizing household electricity costs [97]. A novel method to optimize energy utilization in smart buildings was proposed considering equipment costs, power supply costs, and occupants' comfort [98]. A Time Delay Neural Network with stochastic MPC was developed to enhance energy management efficiency in renewable energy communities [62]. Deep reinforcement learning was used to optimize building energy systems in smart elderly care communities [99].

5.2.5. Research gap 1 - A lack of human-centered design for within-building optimizations

The research of human-centered design is an emerging area and demonstrates a great potential for energy savings. Particularly, occupant behavior, namely human activities that influence building energy use, can influence 50 % of energy use [100]. Scholars have shed light on the influence of energy use behavior on urban energy consumption and have advocated for the enhancement of user energy conservation behavior, for example, hundreds of relevant factors [101]. Retrofit technologies such as smart home control systems are closely related to occupant behavior and they are studied to reduce energy consumption considering occupants' preference, such as thermal comfort, indoor air quality, and appliance usage habit. However, most of the current approaches stay in the operations stage and they are not efficient to incorporate occupant behaviors into the design of building retrofitting technologies, for example, energy simulations [102]. The synergy between smart home, HVAC systems, and building envelopes remains an underexplored domain. Current engineering designs primarily focus on optimizing HVAC and building envelopes in isolation, neglecting the integrated benefits that smart home technologies can provide. A distinct need exists for holistic approaches that simultaneously consider smart home control systems, HVAC systems, and building envelopes to formulate more cost-effective and efficient retrofit solutions. Overall, addressing this gap is inherently challenging, particularly for residents with flexible home behaviors, making accurate predictions of energy use exceedingly difficult to achieve [103]. This gap, in turn, leads to imprecise and often unnecessary retrofit decisions. For example, installing a highly energy-efficiency range may not yield substantial energy savings in cases where occupants infrequently engage in cooking activities at home.

5.3. Focused Area#2: between-building connections – the ties

5.3.1. Power grid

The power grid, as the backbone of modern energy infrastructure, represents between-building connections through electricity networks.

This research identifies three specific technologies to reduce power peak loads and integrate renewable energy sources.

The first refers to demand response, a technology to adjust energy consumption in response to energy network conditions. Dynamic pricing models are the core of this technology [104], which can connect with demand and renewable fluctuations to match supply and demand [105]. A real-time dynamic pricing model for EV charging and discharging and building energy management effectively reduces peak loads [106]. Game theory is used to adaptively adjust the electricity tariff following the changes in electricity consumption [107]. When combining load forecasting models, dynamic pricing schemes enable household load shifting [108]. Notably, the usage of IoT leverages the demand response and optimizes multi-layer grid operations. The IoT approach can incorporate dynamic pricing with energy storage [109], stochastic operation management [110], or HVAC thermal dynamics [111]. Other intelligent approaches include digital twins, min-conflict algorithms, and grey wolf optimization algorithm [112]. A multi-layer interactive optimization model considers individual sensitivity for demand response [113]; and a bi-level scheduling model coordinates demand response with renewable energy [114]. Other demand response strategies connect MPC of HVAC control [115], renewable energy generation [116], and PV scenarios in distribution networks [117]. Recent advancements in demand response have led to practical applications; thus, studies are associated with implementation, such as the evaluation using quantitative key performance indicators [118], social feedback developed in a smartphone app [119], and the profitability of energy service providers [120].

The second refers to energy sharing and trading, the energy redistribution and transactions among individual homes where consumers actively participate in the energy market, potentially lowering costs and promoting the use of renewable energy sources. Energy sharing strategies stand at the core of this technology, for example, simulation-based techno-economic analysis [121], cooperative game theory-based models [122], stochastic linear models [123], and mixed-integer programming models [124]. Notably, intelligent computing plays a very important role to optimize energy sharing and trading decisions, such as RL [125], GA [126], game theory [127], multi-agent systems [128], blockchain [129], VPPs in microgrids [130], IoT sensing [131], and GIS [31]. Associated evaluation studies emerge to explore the impacts of energy sharing on economic, technical, and environmental performance [132], diverse building types, energy market scenarios [133], and stakeholder participation [134]. In addition, research in energy sharing expands to building-vehicle energy interactions, using the augmented ε-constraint approach [135] and Pareto archive NSGA-II [136], and outputs insights into vehicle-to-grid (V2G) [137] and vehicle-to-home (V2H) modes [138].

The third refers to microgrid energy management, which explores optimization and controls of sustainable community microgrids. Microgrid management, especially when connecting distributed energy generators, can achieve energy positive or neutral communities [139], optimize energy trading through innovative negotiation [140], and incorporate IoT schemes in smart grid [141]. The trust-less approach [142], GA [143], PSO [144,145], RL aided Monte Carlo tree search algorithm [146], and the alternating direction method of multipliers were used to optimize energy scheduling for communities [147]. Quantum controlled-NOT gate induced feed-forward neural network [148] was used to accurately forecast energy load and efficiently manage power supply and demand in the smart grid. One work optimized integration of PV, biomass, and storage for a standalone hybrid hospital microgrid [149]. One study designed and analyzed an optimal microgrid configuration with renewable energy and storage technologies [150]. One study assessed the sustainable community shift using distributed energy resources and a community-based market, noting voltage challenges in winter [151]. An energy management concept was introduced that coordinated home energy storage and adjustable appliance usage within a local energy community [152]. Monte Carlo simulation was used to evaluate community shared solar PV under uncertainty [153], while another study optimized renewable sizing in a community microgrid [154,155]. MILP and mixed integer piecewise linear optimization model [155] were used to optimize sizing and operation of distributed energy storage in smart microgrid. Decentralized architectures were investigated for optimizing renewable energy utilization and demand-side management in residential communities [156]. Frameworks were developed for simultaneous optimization of building and distribution grid operations through integrated building-to-grid (B2G) management [157].

5.3.2. District energy system

The district energy system distributes steam, hot water, or chilled water from centralized plants through pipes to buildings. The system represents between-building connections through thermal networks. This research identifies three specific technologies.

The first refers to demand response. Different from the electricity demand in power grid, the demand response here relies on heat generation and heat demand to improve energy efficiency [158]. MPC is important for district energy system due to the high relevance to HVAC networks and building thermal capacity [159]. The integration of MPC can effectively reduce peak loads through controlling return and supply temperatures [160]; and the involvement of demand side management systems can further coordinate supply and demand in an interconnected district energy system network [161]. An intelligent building controller for a district energy system was developed, focusing on demand response strategies to improve thermal comfort and reduce peak energy demands [162].

The second refers to energy sharing and trading, particularly thermal energy trading rather than electricity. Although a few research solely investigated energy sharing and trading strategies in district energy systems, an intelligent network model adopting the concept of heat trading in a district energy system emphasizes the optimization of thermal comfort and energy costs [163], which allows for exchange of excess heat between buildings and overall energy use reduction.

The third refers to energy performance assessment, for example, on the energy saving potential of different strategies for district energy system operation. The impact of various demand side management strategies of district energy system systems on energy saving was analyzed and found limited performance [164]. The potential of high temperature district cooling was examined by data analysis, and it was found to significantly enhance energy saving [165]. A workflow was developed to extract and consolidate housing data from various sources like permits and smart thermostats to support energy mapping and retrofit planning [166]. One study compared centralized district energy systems with multiple sources to decentralized electricity-driven energy systems at the district level, finding that the centralized architecture offers greater robustness [167].

5.3.3. Integrated energy system

The integrated energy system refers to a network where various forms of energy are integrated and interact to ensure a steady and efficient supply of energy to a community. The system represents between-building connections through multiple networks such as electricity, heat, and natural gas. This research identifies two specific technologies to achieve the maximization of overall energy utilization, improve energy efficiency, and reduce energy waste.

The first refers to system optimization, which optimizes the overall capacity and efficiency of multi-energy systems. A new approach for generating various concepts for local energy systems that maximize the use of local renewable resources was proposed [168]. Simulation-based decision support methodologies by means of scenario analysis to facilitate the planning process to realize energy neutral neighborhoods was developed [169]. Overall methodology for transition from traditional historic urban blocks to positive energy block was developed [170]. PSO [171], RL [172] and MILP [173–175] algorithms were used to optimize the operation of polygeneration systems. Some research studied integration of distributed heat pumps [176], thermal energy storage [177, 178], EV charging station [179], and solar energy [178] aiming to optimize the design of polygeneration systems. A novel optimal scheduling model was presented to improve operational flexibility of the integrated energy system by leveraging thermal inertia of buildings and different kinds of auxiliary equipment [180]. A data-driven two-stage distributionally robust optimization model was developed for community integrated energy systems to efficiently coordinate demand response and renewable energy generation uncertainties [181]. A double auction-based peer-to-peer multi-energy sharing and trading mechanism, to conduct the electricity sharing and heat sharing simultaneously, was proposed [182]. A blockchain-based network was presented to improve coordination of both electrical demand management and thermal comfort [183].

The second refers to energy interaction analysis, which optimizes the interactions between different energy networks. One study found district energy systems could increase power system flexibility by reducing peak electric loads and enabling additional hydropower exports [184]. A multi-agent simulation was used to study the interplay between gas and electric systems during building retrofits [185]. A sequential coupling approach was used to assess operations between district energy system and power distribution grids [186]. One study investigated renewable energy communities, showcasing how factors like electrification of heating and transportation can impact energy performance [187]. One study utilized data-driven energy modeling to determine the optimal heat storage capacity for supporting heating electrification, effectively reducing peak power demand and carbon emissions through demand response [188]. Frameworks and key performance indicators (KPIs) were proposed to guide urban energy system planning [189]. In addition, one study used a linear-optimization approach to study the cost difference between shared energy infrastructure and individually planned buildings [190]. One study utilized an improved optimization algorithm to analyze the impacts of different decision maker types on joint electrical and thermal energy scheduling in a community [191].

5.3.4. Research gap 2 - A short expansion of smart home technology into between-building connections

The potential of smart home technology in energy retrofits has predominantly been explored within individual buildings, with a focus on aspects like smart appliance management. However, there is limited attention given to its connectivity between buildings. For instance, the impact of a distributed energy management system on the functionalities of the smart grid, particularly in the context of demand response strategies, remains an often-overlooked gap. This gap signifies a need to understand the interplay between within-building optimizations and between-building connections. Consequently, implementing energy-saving measures solely based on overall energy demand, without considering the specific energy consumption in a multi-building context, may not yield the desired outcomes. For instance, two homes with identical peak electricity loads may differ in load types: the first, equipped with deferrable loads, can leverage demand response to reduce peaks, while the second, with non-deferrable loads, may not derive the same benefits despite displaying similar load patterns. Overall, addressing this gap is crucial for developing effective energy retrofit strategies that extend the scope of smart home technologies across interconnected buildings.

5.3.5. Research gap 3 - A lack of interactive dynamics in the research of between-building connections

Research in the field predominantly emphasizes power grid retrofits, often neglecting district energy systems and their intricate interactions with power grids. This oversight highlights a significant gap in the literature and underscores the need for more integrated studies focusing on their joint retrofitting, considering their inherent interdependence. A comprehensive understanding of the mutual influences of retrofitting both energy networks is imperative for developing stable, optimized solutions and unlocking the full potential of community-wide energy savings. Moreover, recognizing this gap underscores the significance of integrating Combined Heat and Power (CHP) technology into retrofit strategies. This integration holds the promise of elevating overall system efficiency, mitigating emissions, and fostering more resilient and sustainable energy networks. By seamlessly incorporating CHP into the broader discourse on power grid and district energy system retrofits, researchers can pioneer innovative pathways to attain comprehensive and synergistic solutions. This approach aims to maximize energy efficiency and cultivate community-wide benefits. Such an expanded vision accentuates the critical importance of holistic approaches that encompass diverse energy technologies, meeting the evolving demands of community energy systems.

5.3.6. Research gap 4 - A latent between-building connection by social and behavioral networks

Research frequently overlooks the between-building impacts of individual retrofit projects, a gap that becomes increasingly pertinent with the rising trend of energy sharing and trading, amplifying the interconnectivity between buildings. The effects of a retrofit in one building can significantly influence neighboring buildings through these intensified energy links, as well as through social networks. Smart and connected technologies invisibly establish a latent social tie among residents in a community. For example, a smart thermostat will benchmark the temperature settings of other surrounding homes. Therefore, intelligent technologies establish an invisible network of human activities and facilitate the exchange of behavioral knowledge in, such as thermostat setting [8], lighting and appliance use [192], and window opening [193]. All the above behavior knowledge is important for energy retrofit decisions. Understanding these dynamic interactions is crucial for effectively expanding a single building retrofit strategy to encompass the entire community. Overall, we have observed the third important between-building connection – behavioral connectivity – despite the electrical grid and thermal energy grid. Unfortunately, there exists an often-overlooked gap in understanding occupant behavior across multiple buildings.

5.4. Focused Area#3: whole-community integrations – the network

5.4.1. Technology overview

Some studies explored both the retrofitting of buildings and the optimization of energy systems connected to building stocks. One study developed a net-zero building cluster emulator that could simulate energy behaviors of a cluster of buildings and distributed energy systems [194]. Another study evaluated different retrofit interventions for the building stocks as well as the energy sharing between buildings [195]. One study used agent-based fuzzy logic to define and evaluate urban transition scenarios [196]. Overall, whole-community integration is an emerging area, and an increasing number of studies are expected, enabled by recent, advanced computations.

5.4.2. Research gap 5 - few retrofit technologies for whole-community integrations

Current research predominantly focuses on individual facets of energy retrofits, honing in on isolated within-building optimizations (i.e., nodes) and/or between-building energy systems (i.e., ties). This segmented approach overlooks the potential advantages that a holistic perspective can bring. A noticeable gap emerges in the literature when it comes to collectively retrofitting entire communities, involving the integration of power grids, district energy systems, and individual buildings. By amalgamating these elements, researchers can unlock synergistic effects that transcend the sum of individual optimizations. Addressing this research gap is not only essential but also pivotal for fostering effective and comprehensive energy retrofit strategies in the context of smart and connected communities. Embracing a holistic approach ensures that the intricate interactions among power grids, district energy systems, and buildings are thoroughly understood and strategically leveraged to maximize energy efficiency and sustainability at the community level. The knowledge tailored for single building retrofits proves inadequate for large-scale retrofits. Buildings in large-scale retrofits constitute a multi-dimensional complex system – a community connected by technologies and occupants [197]. For instance, buildings constructed at a similar time often employ similar technologies, such as vinyl siding. Large-scale retrofits seek to upgrade the shared technologies across a whole community, introducing standardized elements like prefabricated roof panels that may not cater to each building's customized needs. Consequently, methods used to select retrofit technologies for a single building are unsuitable for a community [198]. Emerging connections and conflicts within the community are not yet well understood [199]. This gap results in knowledge-action bias, value-action bias, and intention-action bias [200]. Bridging this divide is imperative to align knowledge and action, values, and intentions within the intricate dynamics of large-scale retrofits for smarter and more connected communities to maximize energy efficiency and sustainability at the community level.

6. Future research directions

Fig. 7 depicts a roadmap for future energy retrofit research. Milestone one, focused on within-building optimization, has seen significant progress. The ongoing research emphasis is now on milestone two, expanding considerations from individual buildings to interconnections between buildings. Milestone three is the overarching objective, involving the comprehensive integration of whole communities for large-scale energy modeling and simulation.

To attain milestone two, the findings suggest a wide-ranging buildings' retrofit strategy that considers the influence of individual retrofits on neighboring buildings. This entails the understanding of between-building connections for effective energy retrofits. Three key technologies are highlighted to have crucial roles. First, energy simulation tools are essential for modeling the effects of retrofit measures like energy sharing on neighboring buildings, allowing for the assessment of community-wide energy dynamics. Second, network approaches offer insights into how retrofit practices spread within communities, possibly identifying patterns and key influencers in the adoption of retrofit measures. Third, intelligent optimization algorithms can effectively combine network analysis data and energy simulation results to develop optimal retrofit strategies for large-scale buildings. This approach enables a comprehensive understanding of both social influences and energy dynamics, leading to efficient and effective community-wide retrofit solutions.

To accomplish milestone two, the findings highlight the needs for three technological advances. The first need is the analysis of interactive dynamics in energy systems, such as microgrids and district energy systems. This includes an emphasis on optimizing the interplay between different energy systems for energy retrofits. For example, employing co-simulation tools and sensitivity analysis to understand and optimize the interactions between various energy systems, identifying robust, resilient, and effective retrofit strategies under diverse scenarios. The second need is an intelligent optimization framework that can simultaneously consider smart home upgrades, energy-efficient HVAC systems, and building envelope improvements. The framework aims to comprehensively analyze various energy retrofit options, evaluating financial and energy-saving aspects using intelligent optimization algorithms to identify the most cost-effective combination of technologies. The third need is smart home systems for energy efficiency, which not only learn and adapt to individual user habits but also actively guide and influence users toward energy-saving behaviors. This entails leveraging advanced data analytics and machine learning for behavioral analysis in energy consumption. The integration of smart metering and IoT devices is deemed crucial for providing real-time monitoring and feedback on energy use, allowing users to understand and manage their consumption effectively. Additionally, incorporating interactive interfaces and gamification elements can engage residents and motivate energy-efficient practices.

To achieve and excel in milestone three, the findings anticipate growth trends in two research domains. The first domain emphasizes the "whole-community" approach, integrating urban building retrofits with urban energy system optimization by viewing S&CC networks as intricate ecosystems. Optimization strategies in S&CC involve the improvement of physical infrastructure, such as building and energy systems, and the integration of social dynamics to enhance overall network performance. Future focuses could be on employing advanced analytics and simulation tools to understand and optimize the interdependencies in S&CC networks, and/or exploring how technological upgrades in buildings and energy systems are aligned with and supported by social connections within a community, leading to more sustainable, efficient,

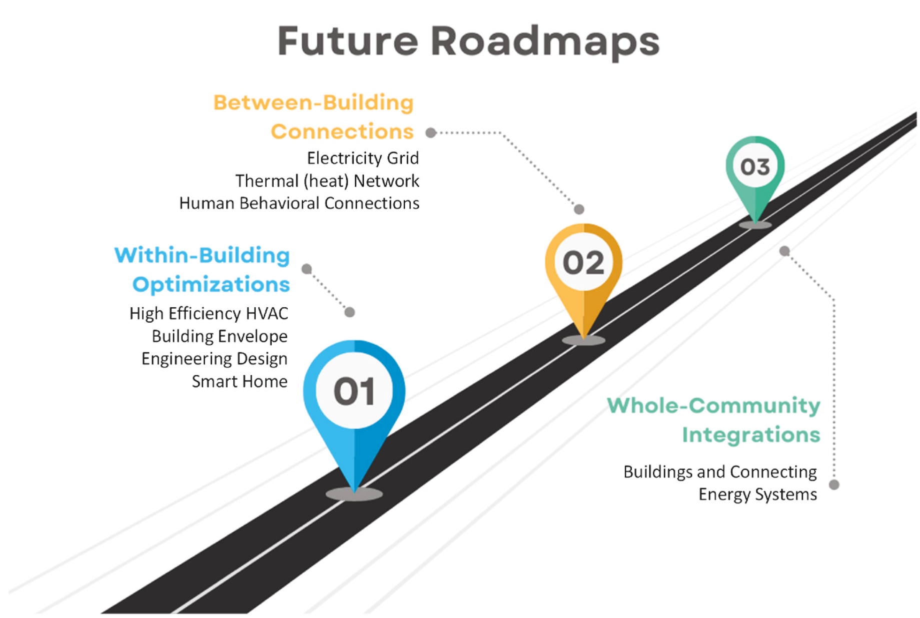

Fig. 7. Future research with three milestones.

and socially cohesive energy solutions. The second domain focuses on integrated research involving PV panels, heat pumps, and EVs to drive urban sustainability transformations. PV panels are commonly used energy saving measures enabling urban sustainable development; however, their intermittent and weather-dependent property restricts energy saving potential. Alongside PV battery storage solutions, load shifting further alleviates PV application limitations. Heat pumps convert electricity into heat, and buildings have thermal storage capacities, so heat pumps can convert immediate electricity into delayed heat. This facilitates building electrification while also enabling electric load shifting. EV can transfer electricity of buildings via charging/discharging facilities, enhancing demand response flexibility and multi-building energy sharing potential. Leveraging heat pumps and EVs promotes electricity flexibility, which can improve solar utilization efficiency.

7. Conclusions

Emerging intelligent technologies enable optimal energy retrofits in future Smart and Connected Communities, showing significant promise for extensive energy savings. S&CC seamlessly integrates intelligent technologies into natural and built environments, gaining importance as US communities enter a transformative era. This research outlines the future landscape of energy retrofits in S&CC, delineating new research scopes and technologies comprehensively. Unlike fragmented reviews, it offers architects, engineers, and builders a crucial, holistic overview essential for navigating the evolving landscape of smart and connected urban development.

A primary finding in this review identifies four research scopes (building construction, mechanical systems, electrical systems and computing, and human-centered design and connectivity), unveiling a novel landscape for energy retrofit research that extends from the built environment to advanced computing, renewable energy, and human-centered connectivity. These interconnected scopes underscore the multidisciplinary nature of research in this area, emphasizing the necessity for collaborative efforts drawing on a synergy of expertise to address the complex challenges associated with large-scale energy retrofit.

Another significant finding unveils a new paradigm of retrofit technologies with three focused areas: Within-building optimizations (e.g., high-efficiency HVAC, building envelope, engineering design, and smart home), Between-building connections (e.g., power grid, district energy, and integrated energy system), and Whole-community integrations. These areas represent the nodes, ties, and interplay within S&CC networks. Notably, advanced computational techniques including AI and IoT hold distinct prominence in the current research approach.

Research gaps have surfaced, collectively shaping the trajectory of urban development. The lack of human-centered design in within-building optimizations calls for a more empathetic approach to improve living experiences. The expansion of smart home technology should embrace between-building connections to foster robust community-level interactive dynamics. The untapped potential of human and behavioral networks in inter-building connections presents an opportunity for deepening community engagement. Moreover, the scarcity of retrofit technologies for comprehensive community integration points to an essential area for innovation in upgrading existing urban infrastructures.

The trend towards S&CC reflects a forward-looking approach, recognizing the potential for interconnected urban ecosystems to enhance overall quality of life, economic opportunities, and sustainability. Researchers are navigating innovative paths amid the evolving urban housing landscape, envisioning a holistic and interconnected experience where technology and social dynamics converge for smarter, more efficient communities. To enable this vision, understanding between-building connections for effective energy retrofits is crucial, requiring advancements in simulation tools, network modeling, and optimization algorithms. Proactive smart home systems guiding energy savings and integrated "whole-community" approaches are growth areas, as is research on transformative technologies like PV panels, heat pumps, and EVs. Exploring these areas and leveraging opportunities brings us closer to realizing the vision of S&CC.

This research is limited due to the focus specifically on technological advancements in building energy retrofits within the context of S&CC. It does not encompass the broader scope of S&CC, including transportation, waste management, water systems, street lighting, and network infrastructure. The exclusion of these sectors from our study is a limitation, as they are integral to the overall energy efficiency of S&CC. Subsequent research endeavors should address these critical sectors to provide a more comprehensive understanding of energy efficiency within the broader framework of S&CC.

CRediT authorship contribution statement

Lei Shu: Data curation, Methodology, Writing – original draft, Visualization. **Yunjeong Mo:** Validation, Writing – review & editing. **Dong Zhao:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

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

Data availability

Data are shared/included in the paper.

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