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Review

An Overview of Emerging and Sustainable Technologies for Increased Energy Efficiency and Carbon Emission Mitigation in Buildings

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Abstract: The building sector accounts for a significant proportion of global energy usage and carbon dioxide emissions. It is important to explore technological advances to curtail building energy usage to support the transition to a sustainable energy future. This study provides an overview of emerging and sustainable technologies and strategies that can assist in achieving building decarbonization. The main technologies reviewed include uncertainty-based design, renewable integration in buildings, thermal energy storage, heat pump technologies, thermal energy sharing, building retrofits, demand flexibility, data-driven modeling, improved control, and grid-buildings integrated control. The review results indicated that these emerging and sustainable technologies showed great potential in reducing building operating costs and carbon footprint. The synergy among these technologies is an important area that should be explored. An appropriate combination of these technologies can help achieve grid-responsive net-zero energy buildings, which is anticipated to be one of the best options to simultaneously reduce building emissions, energy consumption, and operating costs, as well as support dynamic supply conditions of the renewable energy-powered grids. However, to unlock the full potential of these technologies, collaborative efforts between different stakeholders are needed to facilitate their integration and deployment on a larger and wider scale.

Keywords: energy savings; building decarbonization; data-driven; energy sharing; optimal control; grid-buildings integrated control

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1. Introduction

The undeniable evidence of climate change, coupled with the worldwide dedication to environmental decarbonization, has given rise to an imperative need for sustainable transformation of the power sector. Globally, different policies have been developed to tackle the challenge of climate change through the development of greenhouse gas emission reduction targets, deployment of renewable energy systems, the use of energy efficiency measures, and implementation of international agreements such as the Paris Agreement and carbon pricing. Energy efficiency is a central element of such policies because it can significantly reduce greenhouse gas emissions, increase energy security, and promote economic growth. Buildings are among the major players in the energy transition, as they consume around one-third of global energy usage and are responsible for 39% of global carbon emissions [1]. The emissions from buildings are projected to increase in the coming years with the increase in the world population and urbanization, as well as improved energy equality. A number of global commitments and programs are in place to enhance building energy efficiency and sustainability throughout their life cycle [2–5]. One of the leading concepts to achieve energy and carbon reductions in buildings is low-energy or net/nearly-zero energy buildings (NZEBs).

The concept of NZEBs has shown high potential to increase the sustainability of the building sector [6,7]. NZEBs are structures that strive to achieve a balance between their power import and export over the course of a defined period (usually one year) by utilizing innovative design, energy-efficient technologies, and renewable energy resources to significantly reduce their carbon footprint while maintaining a comfortable indoor environment [8]. A key benefit of such buildings is to support the integration of distributed renewable energy resources and minimize power import during peak demand hours.

Characterized by the advantage of reducing the dependence on traditional energy sources, more attention has been paid to NZEBs [6,7]. Wei and Skye [6] categorized different methods and technologies used to achieve NZEBs. It was reported that there are three features, as shown in Figure 1, that can define an NZEB, including the connection of a building with energy infrastructure, a lower-demand building with implemented energy conservation measures, and a building with onsite renewable energy generation sources.

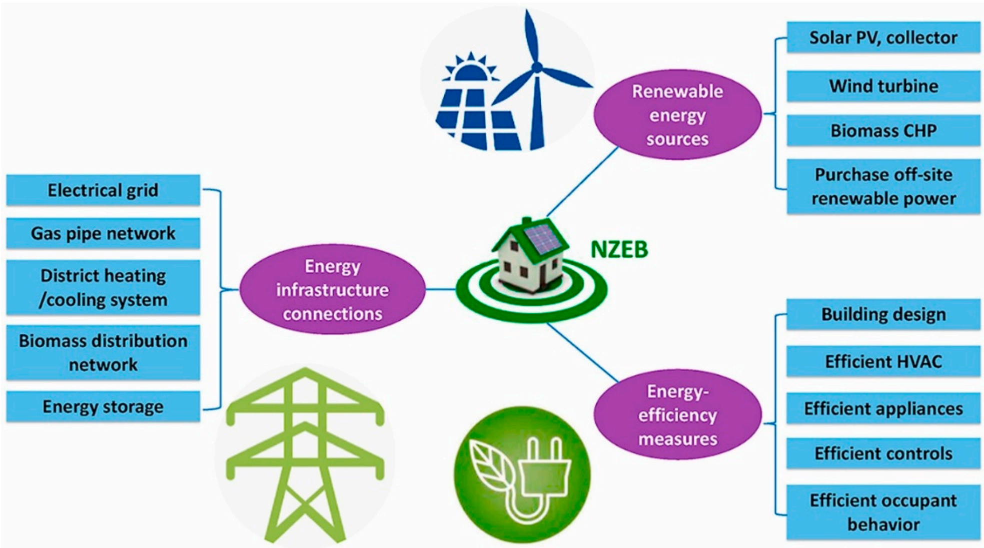

Figure 1. Methods to achieve NZEBs [6].

To achieve NZEBs, a range of energy-efficient solutions and technologies are often needed, which should offer increased energy efficiency and improved demand flexibility. To further support achieving the global decarbonization goals within the built environment, this study aims to explore advances in several emerging and sustainable technologies (Figure 2) for building energy savings and carbon emissions mitigation to enhance building sustainability. The key elements of each strategy and technology are also highlighted, along with the benefits reported in the available literature. It is worthwhile to note that the selection of these emerging and sustainable technologies was based on several key factors and considerations, such as technology maturity, market availability, interoperability, scalability, applicability, long-term viability, and most importantly, carbon reduction and energy reduction potential. Moreover, a systematic approach was adopted to review these technologies by first summarizing the importance of near-optimal sizing of building energy systems using uncertainty-based design. Emerging and sustainable technologies and strategies, along with control schemes, were then discussed, and lastly, grid-buildings integrated control was summarized for decarbonization of the building sector while supporting dynamic supply conditions of renewable-integrated grids.

Figure 2. Illustration of the emerging and sustainable technologies reviewed in this study.

2. Uncertainty-Based Design of Building Energy Systems

Appropriate design of building energy systems is critical to achieving an energy-efficient built environment. The fundamental objective for building decarbonization is to achieve a reduction in energy consumption through energy efficiency measures while meeting energy demand by using renewable energy resources and storage technologies. Therefore, appropriate design of energy systems plays an important role, but current literature shows that most energy systems in buildings were designed based on deterministic conditions [9,10], which may lead to an oversized capacity, and thus, unnecessarily extra initial investment [11].

In traditional design methods, two simplified design approaches, known as the worst scenario and safety factor, are often used [12]. In the worst scenario method, the maximum demand under the worst scenario is used to determine the equipment capacity, which often leads to over-evaluated demand and consequently, the oversized capacity. In the safety factor method, a safety factor is added to the calculated demand at the design condition to determine the equipment capacity, and the reliability of the selected capacity highly depends on the experience of the designers. Despite long practice in engineering applications, these traditional design approaches always lead to oversized systems, which increase initial cost, and, most importantly, energy waste due to low operating efficiency [13].

With the wide deployment of distributed renewable energy generation, the energy systems in buildings are characterized by uncertainties. Discrepancies are always found between the expected performance and field observation due to uncertainties from different factors such as weather conditions and occupancy behaviors [14–16]. These uncertain parameters could be categorized into three different groups [17,18], including outdoor conditions, building construction characterization, and indoor conditions, as shown in Figure 3. These uncertainties directly affect the estimation of both energy demand and generation [19]. Due to the lack of systematic consideration of the impact of uncertainties, inappropriate system configuration could occur in engineering applications [11]. To mitigate this issue, uncertainties should be carefully considered in designing and sizing building energy systems, in particular for NZEBs. Generally, the uncertainty-based design of building energy systems consists of three steps: (1) uncertainty characterization; (2) performance assessment under uncertainties, and (3) multi-objective decision-making. The uncertainty characterization includes the identification of uncertain parameters and the qualification of identified uncertainties. Subsequently, simulations are needed to evaluate the performance of the developed system models under uncertain conditions, enabling the generation of a Pareto solution set based on multiple objectives, such as life cycle costs, energy efficiency, environmental influence, and thermal comfort. The final step involves a comprehensive evaluation and comparison of different design alternatives. The optimal design solution should be determined according to the predefined objectives and alignment of the goals and requirements of stakeholders.

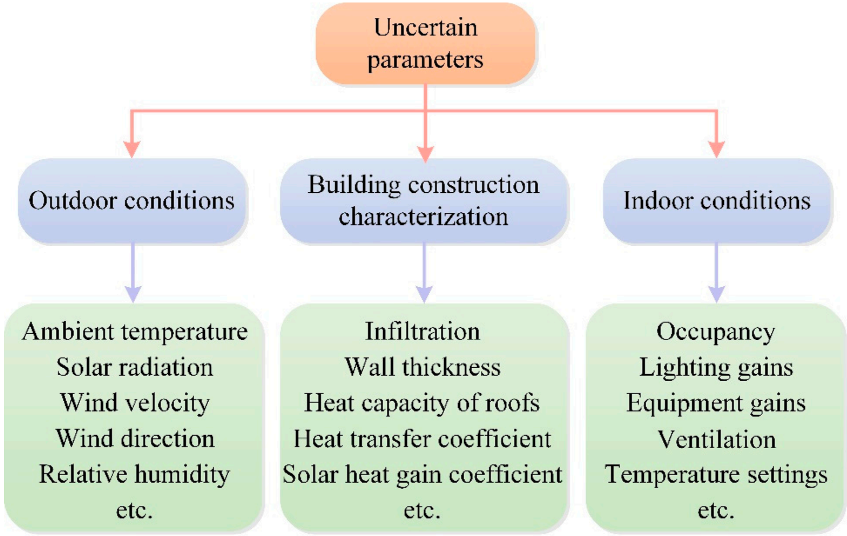

Figure 3. Uncertainties in evaluating building energy demand.

Numerous studies have been reported to optimize the energy systems in buildings by considering uncertainties. Huang et al. [18], for instance, analyzed the life cycle performance of a NZEB under uncertainties. It was concluded that the traditional method cannot achieve the target of nearly zero energy, and 12.61% of life cycle costs can be reduced by using their proposed method. A discrete Markov chain model was proposed in [20] to characterize the uncertainties of electric vehicles (EVs) when determining the capacities and positions of the PV system in a residential building cluster. The results demonstrated that energy sharing greatly improved renewable energy self-consumption, achieving 77% self-consumption and over 20% self-sufficiency. Fan et al. [21] introduced a two-layer collaborative approach using the Monte Carlo simulation for the design and operation optimization of a renewable energy system with hybrid energy storage. The energy system designed for a nearly zero energy community exhibited improved economic and environmental performance, resulting in a reduction of 39.5% and 25.6% in the annual carbon emissions and total annual costs, including investment, maintenance, operation, carbon tax, and renewable energy revenue, respectively. Combining Monte Carlo simulation with the K-means clustering method, Guo et al. [22] proposed a load forecasting method to facilitate the design of a distributed energy system for a nearly zero energy community. It was shown that this method can accurately predict the actual energy demand of end-users. In addition, the designed energy system showed good grid independence with a 36.7% energy import rate only. Zhang et al. [23] developed an uncertainty-based method to size renewable energy systems by taking energy balance, grid stress, and initial investment into consideration. This method demonstrated a 44% improvement in the overall performance of a NZEB when compared to the use of the traditional worst scenario method.

EVs have been identified as a profitable solution to increase building demand flexibility [24]. Despite the increasing share of EVs, their energy demand was only considered in a few studies at the design stage of building energy systems [22,25–27]. EVs are inherently characterized by strong uncertainties [28]. To improve energy flexibility and further investigate potential benefits, more efforts should be made to analyze the effect of EVs on the optimal configuration and sizing of energy systems in buildings. Furthermore, EVs can also be used to support demand management, which can further improve the bidirectional exchange of energy between buildings and the grid [29].

Uncertainty-based design methods can enhance system robustness, reduce unnecessary initial investment, and improve the overall performance of the designed energy systems. Therefore, uncertainties should be considered during the design phase of building energy systems.

3. Sustainable Energy Technologies

3.1. Renewable Energy Integration in Buildings

Renewable energy is a key solution for climate change and building decarbonization. In the roadmap developed by the International Renewable Energy Agency (IRENA), it was suggested that renewables can make up to 60% or more of many countries' total final energy consumption in 2050 [30]. As shown in Figure 4, different renewable energy technologies can be integrated with buildings to meet electricity and heating and cooling demands. Among different technologies, solar energy holds paramount importance due to its abundance and versatility. Its widespread application has been facilitated by favorable policies, significantly reducing the implementation costs of photovoltaic (PV) panels from 4.6 cents/kWh in 2021 to 2 cents/kWh in 2030 [31]. The diversification of solar energy applications has evolved from active to passive technologies. PV systems, prevalent in mitigating power supply pollution, are anticipated to constitute over half of the total renewable energy electricity generation by 2050 [32]. The share of distributed PV generation is continuously increasing. For instance, in 2021, China's distributed PV capacity was 108,580 MW, whereas it was 17,037, 48,559, 48,292, and 42,677 MW for Australia, Germany, Japan, and the United States, respectively. All these countries also have a high capacity for centralized PV generation [33]. PV and photovoltaic/thermal (PVT) systems can be integrated into diverse building elements, including roofs, atriums, skylights, ventilated facades, double-skin facades, and window curtains. Hybrid solar systems that combine active and passive technologies, such as Trombe walls combined with PVs, solar chimneys paired with PVs or phase change materials (PCMs), and PV-integrated ventilation blinds, have also been studied [34]. Although wind energy typically requires expansive open spaces and distance from urban areas, the proliferation of tall buildings in densely populated urban settings has opened new opportunities. Properly spaced tall buildings can harness and transfer wind energy over short distances. Wind energy has the potential to fulfill around 10%–20% of urban tall building energy demand, and urban wind energy systems predominantly comprise wind turbines, typically ranging from 1 to 20 kW, placed on buildings and adjacent grounds [35]. However, careful consideration of local environmental conditions and urban boundary layers is essential for appropriate design and efficient deployment of wind energy systems [36]. Due to the limited initial exploration, many wind turbine projects failed to meet output expectations after a few years of operation [37]. Biomass energy, accounting for approximately 10% of global primary energy demand, represents a vital renewable energy source [38]. Biomass-fired heaters, in conjunction with heat pumps, can provide an economically viable solution for building heating needs. These heaters can cover up to 65% of space heating demand, effectively decreasing reliance on the grid and heat pumps [39]. Furthermore, biomass-derived porous carbon materials resulting from pyrolysis can serve as favorable supporting materials for shape-stabilized PCMs, exhibiting beneficial attributes such as micropore structure, chemical stability, and the potential for integration into construction materials like cement bricks/blocks [40]. There are other types of renewable energy, such as micro-hydro and hydrogen fuel cells, that have been tried in buildings. Micro-hydroelectric systems can harness the energy of flowing water to drive turbines, producing electricity, and are often employed by homeowners in remote areas. While the utilization of hydrogen energy in buildings has not yet been widespread, it is being investigated as a potential means of decarbonizing heating and cooling in buildings. The prevalent approach involves fuel cells, which can generate both electricity and heat for buildings. It is still in its infancy stage, with ongoing projects to explore its potential [41]. However, the adoption of hydrogen energy in buildings faces challenges such as high production costs, limited infrastructure, and safety concerns associated with handling hydrogen, which restricts its widespread integration in buildings [42].

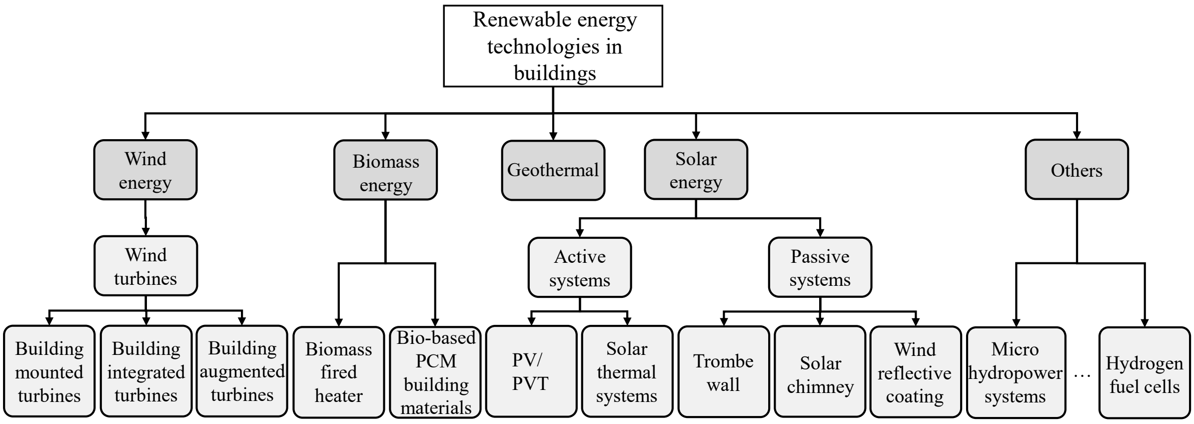

Figure 4. Integration of renewable energy in buildings.

3.2. Thermal Energy Storage

Ensuring a reliable energy supply is imperative due to the inconsistent availability and seasonal variations of renewable energy sources. To address the intermittence of renewable energy supply and temporal disparities, thermal energy storage (TES) has emerged as a promising solution. The ability of TES systems to provide flexible assets to wind and solar energy resources increases the overall value of TES in the modern energy supply chain. The 2020 innovation outlook on thermal energy storage published by the International Renewable Energy Agency (IRENA) [43] demonstrated that the TES global market will grow to triple the current size by 2030, which indicates an increase from 234 GWh in 2019 to 800 GWh within a decade. Moreover, it is expected that the investments in TES technologies for cooling and power applications will surge from 13 billion USD to 28 billion USD in the same period [43]. In buildings, TES can be mainly used for demand shifting and load modulation through integration with heat pumps and hot water storage systems as well as with building envelopes [44].

Sensible and latent energy storage systems are the two major TES systems used in buildings. Sensible energy storage systems require large volumes compared with that of latent energy storage systems. However, currently, sensible energy storage systems in the form of hot water tanks are among the most used TES systems in buildings because of their low cost and low complexities [45]. Research has shown that latent energy storage systems are more effective than sensible energy storage systems, and they can be used in different ways to enhance the overall thermal performance of buildings and building energy systems. Phase change materials (PCMs) have demonstrated high performance and practicality to be used as the leading latent energy storage medium in building applications. Figure 5 illustrates different applications of PCMs in buildings, where PCMs can be integrated with building envelope and building energy systems for enhanced performance.

Various benefits and limitations associated with the use of PCMs for different applications in buildings have been reported. For instance, in [46], it was illustrated that the integration of PCMs with gypsum and wallboards can result in enhanced reliability and durability over extended durations, though with drawbacks, such as potential deposition of volatile pollutants on surfaces and limited fire resistance. Another study demonstrated that the excessive use of hydrated salt PCMs in concrete can jeopardize material strength, but incorporating paraffin can enhance thermal storage while maintaining compressive strength [47]. Recommendations for improving thermal efficiency and mitigating supercooling involve the introduction of an internal ventilation system within PCM roof and floor systems to enhance convective heat transfer across the PCM surface [48]. For optimal energy efficiency, lighter mass PCMs are suggested when combined with air conditioning systems to minimize undesired heat transfer between upper and lower PCM layers. Furthermore, a well-designed operational strategy for the combined air conditioning-PCM system can significantly improve the overall energy performance [49]. The effective integration of PCMs into bricks requires the selection of PCMs with melting temperatures closely aligned with room temperature to maximize performance enhancement [50]. Thin PCMs with expansive heat transfer areas are preferred over thicker alternatives within bricks, and a staggered arrangement of PCMs can enhance the heat exchange between the PCM and brick materials [51].

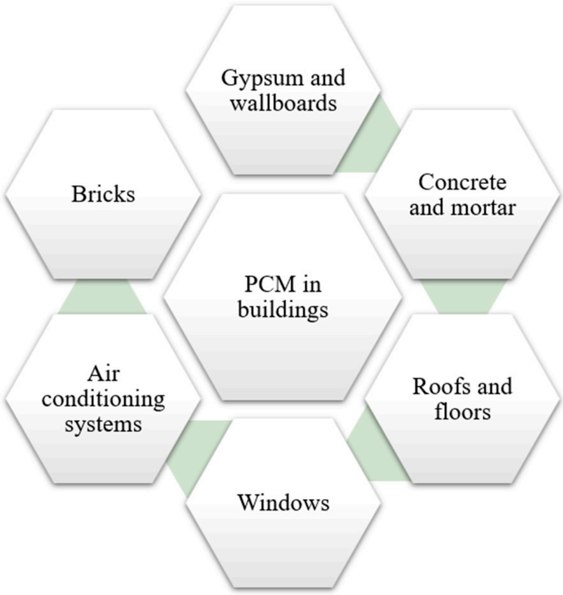

Figure 5. Integration of PCMs in buildings.

A range of studies have also demonstrated the high value of TES systems in increasing the efficiency and demand flexibility of buildings and building energy systems, contributing to the reduction in overall building emissions. For instance, in [52], a TES system filled with a PCM was used to shift the peak demand of an HVAC system to off-peak demand hours. The results showed that the TES system integration with the HVAC system helped reduce peak demand by 73% and provided 37.1% cost savings for the analyzed period. Tuncbilek et al. [44] reviewed a number of studies involving the use of TES for enhanced flexibility of buildings and building energy systems. The review demonstrated that the use of TES can reduce overall energy consumption, operational costs, and emissions of buildings. Overall, the TES systems will be a central part of decarbonizing the building and power sectors, along with providing opportunities to reduce overall operating costs and increase energy efficiency. However, lack of technology readiness, awareness, policy, and market mechanisms are among the main bottlenecks that are important to be addressed to explore the full potential of TES technologies in building applications [43].

3.3. Heat Pump Technologies

Heat pumps are increasingly recognized as a key and cost-effective solution for the electrification of heating systems and tackling carbon emissions, supporting the goal of achieving a net zero energy future [53]. The International Energy Agency (IEA) estimated that the installed number of heat pumps will rise from 180 million globally in 2020 to around 600 million in 2030 [54], and heat pumps could reduce global CO_2 emissions by at least 500 million tons in 2030 [55]. A recent report published by the Australian Energy Efficiency Council and the Australian Alliance for Energy Productivity concluded that ambitious deployment of heat pumps in different buildings and industrial processes could reduce energy usage by up to 14,391 PJ and save 746 Mt of greenhouse gas (GHG) emissions by 2050 [56].

Heat pumps are generally energy-efficient and can be powered by renewable energy resources. They can be easily integrated with thermal energy storage systems for load management, such as load shifting and peak demand reduction. Different types of heat pumps are now available in the market. According to the types of heat sources used, heat pumps can be classified into air-source heat pumps, water-source heat pumps, and ground-source heat pumps. It is noted that ground-source heat pumps are simply a variation of water-source heat pumps that are capable of working with a broader range of source water temperatures. Other heat pumps include absorption heat pumps and desiccant heat pumps. An absorption heat pump is a heat pump driven by thermal energy instead of electricity. It is most cost-effective when low-cost thermal energy is available and in applications where access to electricity is expensive. Desiccant heat pumps are developed based on the vapor compression cycle but with desiccant materials coated on heat exchangers for dehumidification. Such heat pumps are suitable for applications with strict humidity control and in tropical and subtropical climate conditions.

Among different heat pump technologies, ground-source heat pump (GSHP) systems are receiving increasing attention [57,58] as they can take advantage of the relatively stable earth temperature to achieve heat extraction from or heat rejection to the ground through ground heat exchangers to meet different air-conditioning requirements. The long-term operation of stand-alone GSHP systems may lead to ground thermal imbalance, resulting in system performance degradation [59]. Hybrid GSHP systems assisted with supplementary devices have been considered to be a solution to alleviate soil and system performance deterioration [60]. In addition to environmental and energy performance improvements brought by the application of auxiliary devices, obvious economic benefits can also be achieved, especially in terms of cost savings in the upfront purchase and installation of ground heat exchangers [61,62]. As shown in Figure 6, different auxiliary devices can be coupled with GSHP systems [63] to increase the overall efficiency and mitigate ground thermal imbalance.

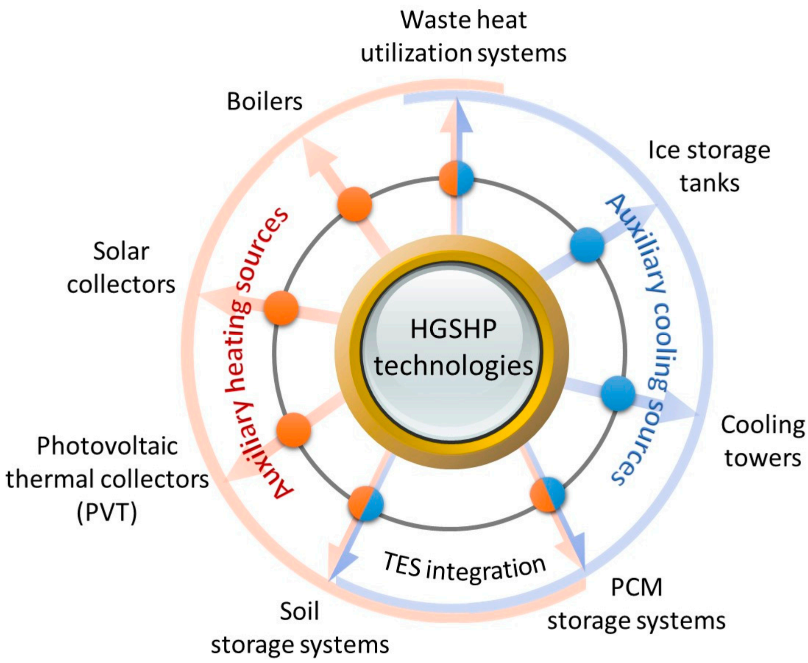

Figure 6. Hybrid GSHP systems integrated with different auxiliary devices.

Heat pumps will remain the main solution to provide heating and cooling to buildings in the coming decades, and cost-effective solutions/strategies to further improve their efficiency are needed. Solar heat pumps are also among the interesting solutions.

3.4. Thermal Energy Recovery and Sharing

Thermal energy recovery and sharing can capture waste energy from one system and redistribute the captured waste energy to nearby systems or end-users [64]. Figure 7 illustrates an example of a thermal energy recovery and sharing system. Such a system can provide simultaneous cooling and heating to interconnected networks of different buildings or utilities, leading to enhanced energy efficiency and reduced carbon emissions. Thermal energy recovery and sharing systems can effectively harness and re-utilize otherwise wasted energy and further improve resource utilization and sustainability [65].

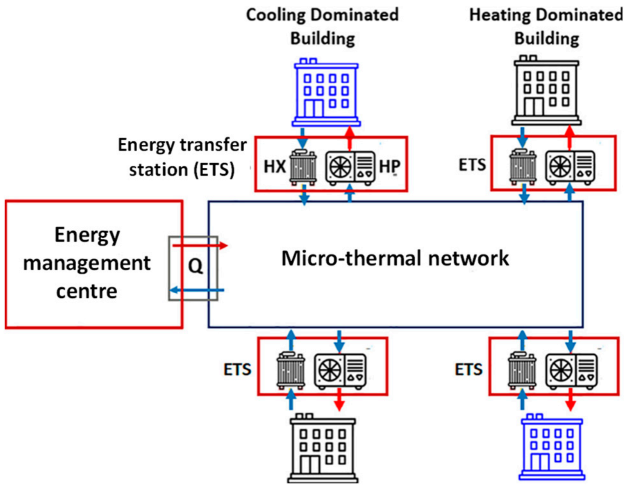

Figure 7. Illustration of a thermal energy sharing system, where HX represents the heat exchanger, and HP indicates the heat pump [64].

The cooling-dominated buildings or utilities in thermal energy sharing systems can include cooling systems of data centers, ice sports centers, and supermarkets, as well as industrial processes. Data centers can produce a substantial amount of waste heat during the cooling process of their equipment [66]. The temperature of this waste heat varies depending on the different types of cooling systems employed [67]. The cooling systems in supermarkets and ice rinks can also generate a significant amount of waste heat by providing the necessary cooling energy, and the waste heat from supermarkets can reach temperatures of more than 50 °C [68–70]. Many industrial processes also generate significant amounts of waste heat, often at high temperatures, making them a potential heat source [71]. These potential heat sources often exhibit stable and large heat generation characteristics, providing ample opportunities for integration into thermal energy recovery and sharing systems.

One notable utilization of waste heat is to supply thermal energy for heating purposes, such as integrating with district heating (DH) networks [72,73] and preheating swimming pools [74,75]. Recent studies have demonstrated the potential benefits of thermal energy sharing systems. Pan et al. [76] examined the performance of an adsorption chiller, which was powered by thermal energy recovered from a data center. Araya et al. [77] presented a lab-scale Organic Rankine Cycle (ORC) system, which was designed to operate using low-grade waste heat obtained from a server rack within a data center. Abdalla et al. [64] introduced a reduced model of a thermal energy sharing system, which effectively allowed thermal energy to be shared among different facilities. It was found that such a system could fulfill 48% of the overall heating demand, and by incorporating a water tank, an additional 12% of thermal energy could be covered, resulting in a remarkable 74% reduction in total carbon emissions. In another study by Wirtz et al. [78], an optimal design approach based on Linear Programming was developed for the design of the 5th-generation district heating system, as shown in Figure 8. It was found that the optimized system achieved a remarkable 42% cost reduction and an impressive 56% decrease in carbon emissions through component selection and optimal sizing. Similarly, a study described in [79] focused on thermal energy sharing between the cooling system of a data center and a multi-unit residential building. The findings indicated that energy sharing reduced the heating requirements of the building by 55% and the cooling requirements of the data center by 50%. Zhang et al. [80] developed an economic evaluation model for waste heat utilization of data centers in district heating networks. It was reported that reusing waste heat from data centers could achieve both economic and environmental benefits. Li et al. [81] examined two thermal energy storage methods in thermal energy sharing systems, including short-term storage using a water tank and long-term storage using a borehole thermal energy storage system. The water tank was found to effectively reduce peak loads by 31% and lower annual energy costs by 5%, and the borehole system can increase waste heat utilization from 77% to 96% and achieve an annual reduction of 8% in CO_2 emissions. By dynamically optimizing the parameters of the water tank, an optimal storage size was determined by considering the trade-off between the payback period and heating cost savings. It was found that prosumers could save up to 9% of their annual heating costs [82]. Wang et al. [83] proposed an efficient system using CO_2 direction-expansion GSHPs to harvest the waste heat from a data center for heating surrounding buildings. It was found that this system could reduce energy consumption by nearly 50% when compared to air-source heat pumps.

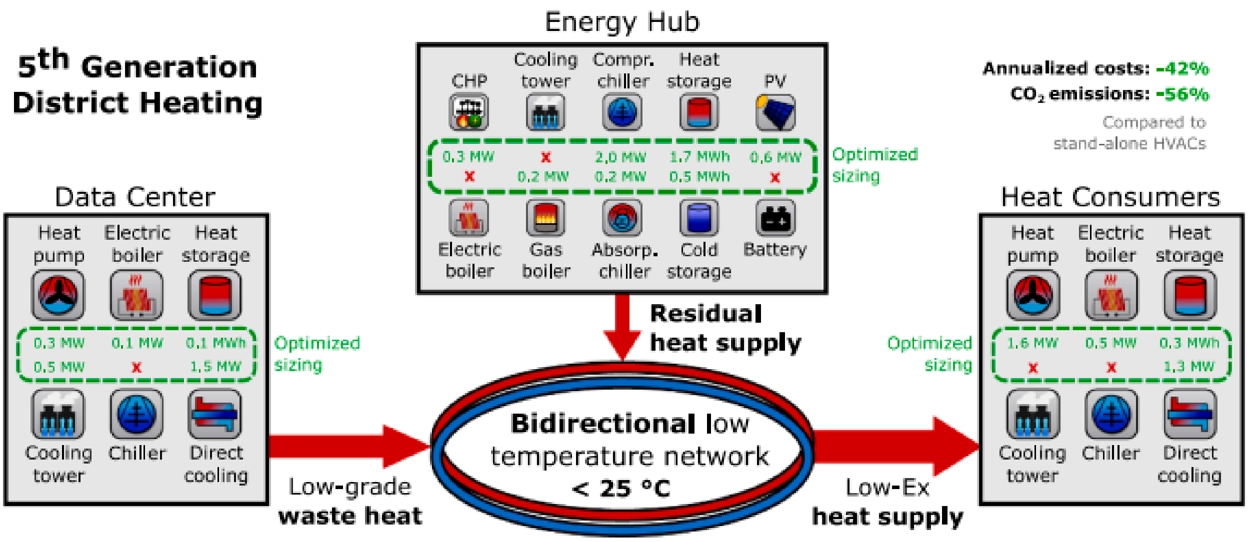

Figure 8. The 5th generation district heating system [78].

In addition to thermal energy sharing, electricity generated by distributed renewables can also be shared among different buildings. In summary, while thermal energy recovery and sharing systems showed significant advantages in terms of GHG reduction, cost savings, energy efficiency, and waste heat utilization, further research is needed to fully explore opportunities to increase their overall performance.

3.5. Retrofits for Increased Energy Efficiency

Most buildings are existing buildings, and retrofitting of existing buildings has been widely accepted as one of the effective measures to achieve building decarbonization. According to a report recently published by Market Research Future [84], the global energy retrofit systems market was valued at USD 150.9 billion in 2022, and it was projected to increase to USD 272.8 billion by 2032 with a compound annual growth rate of 6.8% from 2023 to 2032. In general, there are two types of retrofits, including shallow retrofits and deep retrofits. Shallow retrofits focus on small alternations by using low-cost or no-cost energy conservation measures, while deep retrofits focus on major renovations, and a holistic approach is often required to systematically explore co-benefits from energy retrofits and determine the best retrofit options. A recent study showed that stock-wide implementation of deep retrofits in existing buildings of eight cities (i.e., Braga, Cairo, Dublin, Florianopolis, Kiel, Middlebury, Montreal, and Singapore) can reduce energy use and carbon emissions by up to 66% and 84%, respectively, without additional grid decarbonization efforts [85]. Based on the review of energy retrofit policies for the UK's existing buildings, it was concluded that deep retrofits are needed for most UK's existing housing stock to bring more flexible financing schemes and reduce carbon emissions [86]. Figure 9 illustrates an example of deep retrofit of a typical Australian timber framed fibro house to a state-of-the-art net zero energy home through a combination of architectural alternation, envelop renovation, facilitating daylighting and natural ventilation, and integration of renewable energy systems and highly efficient air conditioning solutions.

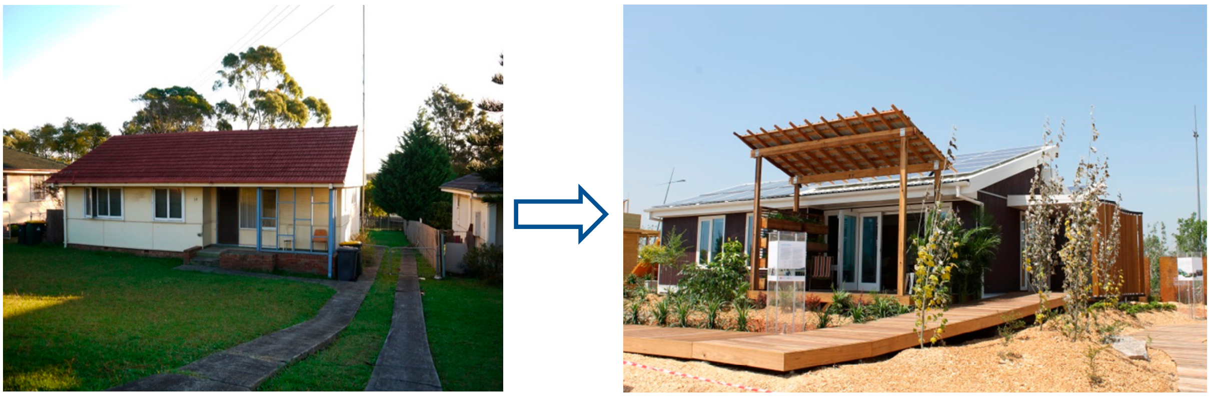

Figure 9. Illustration of deep retrofit of a typical Australian timber framed fibro house.

In the past, the selection and quantification of co-benefits of retrofit measures were often achieved with the assistance of energy auditing, building performance simulations, and domain expertise. With the continued development of low-cost sensors, massive data can be readily available from existing buildings, and this presents significant opportunities to use machine learning and big data analytics to optimize the retrofit process and explore energy-saving potential. Figure 10 summarizes different retrofit methodologies for large-scale building retrofits [87]. Based on the data collected from existing buildings, the bottom-up approach focuses on retrofitting individual buildings by analyzing different retrofit strategies and then extrapolates the results to larger scales, while the top-down approach focuses on using the available datasets to explore retrofit potential, establishing benchmarks, and providing guidelines for the development of energy retrofit policies [88].

To maximize the benefits of existing building retrofits, significant efforts are still needed. More rigorous retrofit methods should be developed to optimize the selection of the most cost-effective retrofit options. Although many retrofit techniques can reduce building energy consumption and carbon footprint, their longevity has rarely been considered [89]. Circular economy is the key to sustainable development, and applying circular economy principles to building retrofits is an interesting direction to reduce the use of building materials and provide significant carbon benefits. The availability of large datasets from existing buildings will offer great opportunities to use state-of-the-art machine learning methods and big data analytics to explore useful information, providing new potentials to support the decision-making process and accelerating the selection and optimization of retrofit measures.

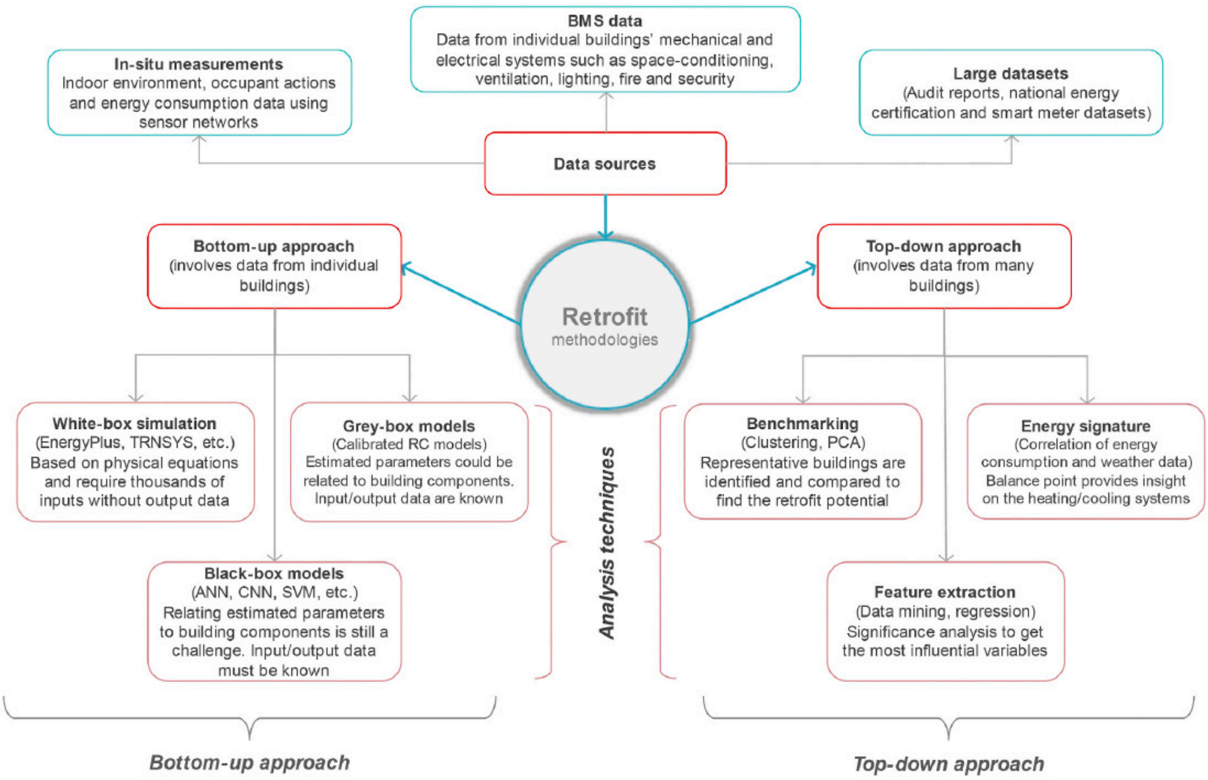

Figure 10. Illustration of different retrofit approaches [87].

4. Data-Driven Modeling, Demand Flexibility, and Integrated Control

4.1. Data-Driven Modeling

Data-driven modeling has evolved as one of the leading approaches for real-time control of buildings. Machine learning algorithms used for data-driven modeling can be generally categorized into two groups, including shallow structure machine learning and deep learning [90]. Generally, both categories of machine learning algorithms aim to identify correlations between model input and output variables, while deep learning employs more complex model structures and numerous parameters and can result in more powerful feature representation capabilities with lower interpretability and transparency [91]. A detailed comparison between the use of shallow structure machine learning and deep learning for building energy modeling can be found in [92]. Due to their superior ability to capture complex data features, two deep learning models, i.e., Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), have been frequently adopted to predict various building variables [93]. RNN models, such as LSTM networks, have shown outstanding performance in building energy consumption prediction due to their superior capacity to capture long-term temporal dependencies in sequential data [94–96]. CNN models have been highly successful in capturing spatial features, making them particularly well-suited for graphic data analysis. It was reported that a CNN model trained by sky image data can effectively improve the prediction accuracy of PV power generation as compared to conventional data-driven models [97].

In addition to the deployment of advanced deep learning algorithms, model fusion in data-driven modeling has emerged as a promising research area and has shown good performance in building energy management. In [98], a combination of an LSTM model and a CNN model was employed to simultaneously extract spatial and temporal features of model inputs, which led to increased accuracy in the predictive modeling of a GSHP system. In [99], building energy consumption was decomposed into a global part, a local part, and white noise. The global part was attributed to the typical user behavior of a building, while the local part was attributed to non-typical activities. A static deep learning model was used to predict the global part based on weather and time-related variables at a given time, while an auto-regression (AR) model was used to predict the local part using time series data of the local part as the input. The entire process is illustrated in Figure 11. This approach achieved superior performance when compared to the strategy that either used deep learning or AR models alone.

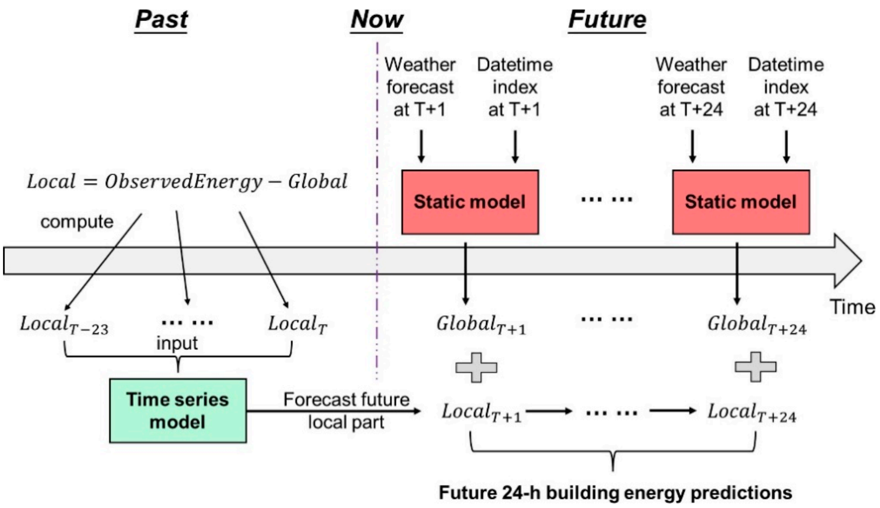

Figure 11. A hybrid machine learning model for building energy consumption prediction [99].

In [100], the integration of an LSTM model and a reinforcement learning (RL) model was explored to enhance the adaptability of deep learning prediction models. This integration allowed for dynamic updating of model parameters according to the most recent prediction errors during the prediction process, leading to improved accuracy in the prediction of building energy consumption. In [101], domain knowledge and decision trees were incorporated into an RL model to optimize building operations for improved energy flexibility. It was found that this method was effective in improving learning efficiency and model interpretability. Furthermore, the recent success of attention mechanisms has resulted in the increasing popularity of their integration with data-driven modeling. Attention mechanisms have been successfully used to improve modeling accuracy [102] and model interpretability [103] for data-driven modeling of building energy systems.

As the development of reliable data-driven models in practice is often limited by the scarcity of model training data, the solutions to address data scarcity for data-driven modeling have also been increasingly explored in recent years. A transfer learning scheme was developed for non-intrusive load monitoring in smart buildings [104]. The method reduced the data dependency of predictive modeling for energy consumption of indoor appliances. In [105], a meta-learning model, also known as the 'learning to learn' approach, effectively reduced the requirement of training data in the prediction of personalized thermal comfort conditions. In [106], Generative Adversarial Networks (GANs) were employed to generate synthetic data to train predictive models of building electricity demand and successfully alleviated data scarcity issues for data-driven model development.

The approaches explored in the above literature provided valuable references for the development of data-driven models for building energy management. Machine learning can learn patterns and relationships in complex datasets, enabling the development of accurate predictive models without explicit programming. However, they are prone to overfitting if they are not properly regularized or validated, and the results can be challenging to interpret and explain in comparison to the use of traditional statistical models. Appropriate selection, training, and optimization of machine learning models for a given application is critical.

4.2. Building Demand Flexibility

Demand flexibility of a building is its ability to manage its energy demand and generation based on user needs, grid requirements, and local climate conditions [4]. It can allow end-users to decrease, increase, modulate, or shift energy consumption to modify their load profiles using flexible load and/or onsite generation and storage sources, and is an attractive resource to provide grid support services and smooth out the so-called "duck curve" of power systems (Figure 12) while meeting interests and objectives of end-users such as energy availability, decreased energy costs, and reduced carbon emissions [107].

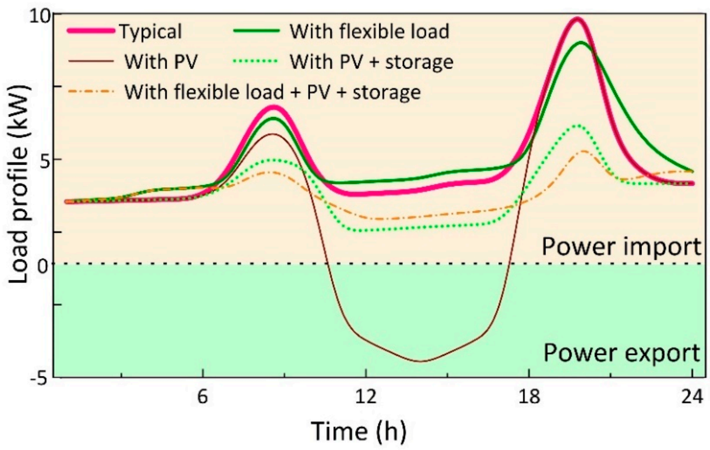

Figure 12. Indicative illustration of how load profiles can be modulated through demand flexibility.

Flexible demand is a viable component of "non-wires alternatives" and is a low-cost resource to effectively support power balance and accelerate renewables penetration in the energy mix. Demand flexibility in buildings can be greatly increased by using onsite generation, energy storage, and controllable loads, and can help reduce energy costs of end-users according to different flexibility types and demand management strategies (Figure 13) relating to flexibility capacity, duration, and response speed. By reducing and shifting the timing of electricity consumption in the grid-interactive efficient buildings, a 6% carbon emissions reduction in the US power sector can be achieved by 2030 [108]. The introduction of a Smart Readiness Indicator (SRI) to promote smart buildings with the capacity to provide demand flexibility and linking the SRI assessments to the Energy Performance Certificate in the building sector in Europe can result in final energy savings of up to 198 TWh by 2050 and 32 million tons of avoided carbon emissions per year [109]. A study for 498 residential homes showed that using battery and demand flexibility through home energy management systems along with energy efficiency upgrades can save households up to $590 in annual electricity costs [110].

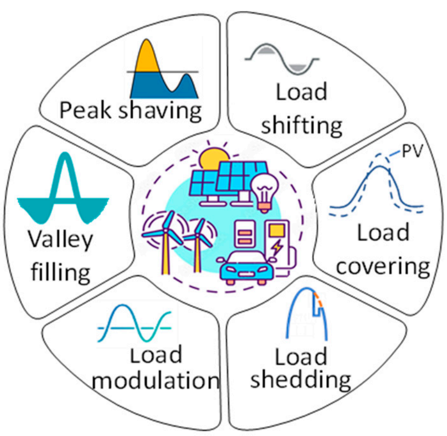

Figure 13. Various demand management strategies.

However, how to effectively use demand flexibility to manage energy consumption and how to actively participate in demand side management remain unclear for many residential customers. Many current studies have demonstrated the high value of using different flexible sources for demand management [111–113], but it remains critical to develop a generic characterization and optimization framework for enhanced demand flexibility and demand management. To ensure successful characterization and optimization of building demand flexibility, a holistic approach is required. This involves collaborations between architects, engineers, energy analysts, and stakeholders to design and implement energy-efficient building systems and practices. Continuous monitoring, data analysis, and performance evaluation are also vital for refining strategies and adapting to evolving energy landscapes.

Figure 14 illustrates a general process to characterize and optimize demand flexibility in buildings. Characterizing and optimizing building demand flexibility involves a comprehensive analysis and enhancement of a building's ability to dynamically adjust its energy consumption and generation patterns in response to external factors, grid conditions, and operational needs. It requires an in-depth understanding of a building's energy systems, envelope, occupant behavior, and the potential for integrating renewable energy sources and energy storage systems. Characterization involves the collection and interpretation of data related to occupancy patterns, thermal performance, equipment efficiency, weather data, energy demand profiles, and potential integration of smart technologies [113]. This information helps identify opportunities for demand response, such as load shifting and peak shaving. It also involves the use of different technologies and solutions for enhanced demand flexibility along with the quantification of the achieved flexibility. For instance, the integration with smart grid technologies enables a building to respond to signals that incentivize energy conservation during peak demand periods or take advantage of surplus energy during off-peak hours [114]. Furthermore, the implementation of energy-efficient HVAC systems, smart lighting, and automated shading systems can contribute to improved demand flexibility by reducing overall energy consumption and improving indoor thermal comfort [115–117]. Energy storage solutions, such as batteries or thermal storage systems, can play a crucial role in improving building demand flexibility through strategically managing stored energy, reducing their reliance on the grid during peak hours, and contributing to overall grid stability [111]. Characterization of demand management based on different sources and their potential benefits can help select optimal flexible systems for enhanced flexibility.

Optimization of building demand flexibility involves the development and deployment of advanced control strategies. This can be achieved through utilizing predictive algorithms, machine learning methods, and real-time monitoring to predict energy demand and supply variations [118–120]. Simulation models can also be opted for to optimize the flexibility potential of a building.

4.3. Improved Building Control

Appropriate building control is essential to ensuring service systems provide functional requirements with the least energy consumption. According to a study by Afroz et al. [121], appropriate control can reduce 25% of energy use of an HVAC system. Control strategies for buildings can be generally categorized into rule-based control, model predictive control, reinforcement learning control, and data-driven predictive control. The majority of the control strategies developed for buildings were focused on HVAC systems as HVAC systems are the major energy consumers in buildings.

Rule-based control is the most basic control strategy. It can provide safety limits and is easy to implement. Although rule-based control strategies have been widely used in practice, they largely rely on predefined rules and can only offer limited opportunities to enhance the performance and operating flexibility of building HVAC systems. Model predictive control (MPC), which uses models to predict future performance and make optimal control decisions, has attracted increasing attention in recent years due to its predictive feature. For instance, Fiorentini et al. [122] proposed a two-level MPC method to maintain indoor thermal comfort and reduce the energy use of an HVAC system. The high-level controller with a one-day prediction horizon was used to select the control modes of the system, and the low-level controller with a five-minute prediction horizon was used to make operational decisions. Merema et al. [123] developed a two-level MPC strategy to control the HVAC operation. The two-level MPC strategy included a black-box linear model with auto-regression and a grey-box resistor-capacitor nonlinear model to predict building thermal comfort. The method was tested in a real lecture room, and it was shown that this MPC strategy can reduce electricity consumption by 10–40%.

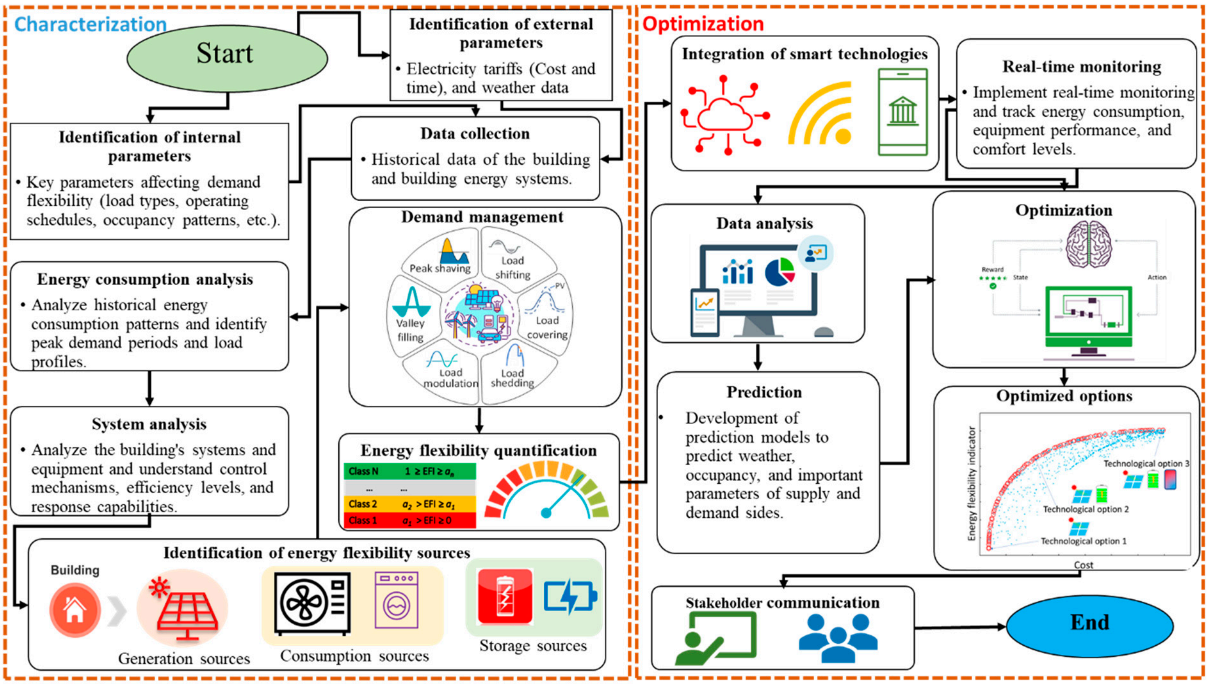

Figure 14. Characterization of demand flexibility and optimization of building demand management.

Reinforcement learning, which can directly establish a relationship between the inputs and outputs, has recently received increasing attention. Wei et al. [124] developed a control strategy by using deep reinforcement learning (DRL) to reduce energy costs and improve indoor thermal comfort. The DRL strategy was tested based on the EnergyPlus simulation of a physical house. Compared with rule-based and MPC strategies, this DRL strategy can reduce energy use by 27%. Azuatalam et al. [125] used a demand-response reinforcement learning method to control the operation of an HVAC system. In their study, proximal policy optimization was used to stabilize the hyper-parameters of RL agents in order to build a relationship between occupancy of the building and HVAC operation decisions. The method was tested in EnergyPlus, and it was shown that it can reduce 22% of energy use when compared with a handcrafted baseline controller. Yu et al. [126] proposed a DRL method using a multi-actor-attention-critic method to optimize the HVAC control of multiple-zone buildings. The method was tested using real-world data of energy prices, ambient air temperature, and zone-occupancy data. It was indicated that this control method was effective in controlling multiple zones' thermal comfort and reducing energy costs.

A data-enabled predictive control (DeePC) method was recently proposed to solve the high training cost of reinforcement learning [127]. The DeePC method used a non-parameter learning method to predict future trajectories. This method was not developed based on learning from a large dataset but on using trajectories for system identification. It can perform better in nonlinear stochastic systems with regularizations. Chinde et al. [128] used a DeePC method to optimize the operating parameters of a building HVAC system. The method was tested via an office prototype building in EnergyPlus simulation. Compared with a traditional MPC strategy, the operational cost of the HVAC system by using this method was reduced by 5% in a five-week test. The strengths and weaknesses of the commonly used strategies for building HVAC control are summarized in Table 1.

Table 1. Strengths and weaknesses of different control strategies for building HVAC systems.

Control Strategies	Strengths	Weaknesses
Rule-based control	Easy to implement and understand; and can enable safety rules to the control system.	Low flexibility to change setpoints to react to demand variation; and cannot provide global optimal solutions.
Model predictive control	It enables safety rules; reacts prior to variation to improve stability; and has high flexibility to meet control requirements.	High computational costs; and relies on accurate models for prediction.
Reinforcement learning	Model-free data-driven method; does not require much information for model development; and requires low reaction time for decision-making once trained.	Requires long training time and large training dataset; and doesn't enable safety rules.
Data-enabled predictive control	Does not require a large training dataset; and has high stability for nonlinear time-varying systems.	Has not been widely validated for HVAC control; and the efficiency of the model relies on the quality of the training data.

4.4. Grid-Buildings Integrated Control

To support grid operation, future buildings integrated with variable renewable generation sources should have the capability to regulate their demand according to the needs of the grid. To achieve this, a bidirectional interaction between the grid and buildings is required, which is different from the conventional unidirectional electricity flow from the grid to buildings. This bidirectional dynamic interaction can potentially result in a range of severe issues for the grid, including harmonic distortions, unbalances, voltage flicker, and other complications, and in extreme cases, it may even lead to grid collapse [129,130]. To address these issues, substantial efforts have been made to explore control strategies for grid integration of sustainable buildings. By adopting such strategies, buildings can effectively tackle the complexities associated with bidirectional energy flow. This approach enables seamless coordination between the building and the grid. It ensures efficient resource utilization while minimizing any adverse effects on the grid. Such control strategies can allow buildings to interact harmoniously with the grid, paving the way for optimized energy management and reduced environmental footprint [131]. In general, there is a relationship between energy efficiency and grid interactivity, which can be achieved by using smart control for energy management [132].

Grid-buildings integrated control systems are increasingly recognized as essential for optimized energy usage and improved reliability and efficiency of sustainable buildings. In contrast to building control, grid-buildings integrated control allows for real-time optimization of energy usage based on grid conditions, integration of renewable energy sources, effective utilization of energy storage systems, and provision of grid support services, leading to cost savings and increased resilience [133]. Grid-integrated buildings can be classified as microgrids. Microgrids are localized energy systems that operate either autonomously or in parallel with the main electrical grid [134]. They consist of interconnected loads, distributed energy resources, and advanced control strategies. In this context, grid-integrated buildings exhibit characteristics aligning with the microgrid concept. Control strategies developed for microgrids can be applied to grid-integrated buildings and vice versa.

A wide range of computational and experimental aspects related to the integration of buildings into the grid have been the subject of numerous studies. Huo et al. [135] proposed a two-level hybrid decentralized-centralized (HDC) strategy to control distributed energy resources in grid-interactive efficient buildings. This HDC algorithm can offer a scalable and bifurcated approach to managing a large number of grid-connected buildings and devices. The two-level design consisted of central aggregators that manage buildings and a system operator that coordinates the distribution network in a decentralized manner. Rastegarpour and Ferrarini [136] analyzed different modeling and control techniques to address building energy efficiency and management problems. The importance of adaptive control techniques and real-time predictive models in optimizing energy usage and integrating buildings into smart grids was highlighted. Figure 15 shows the control hierarchy and levels of integration of building components to the grid over a time period ranging from a week to one second. The yellow zone shows the area where the system behaved dynamically.

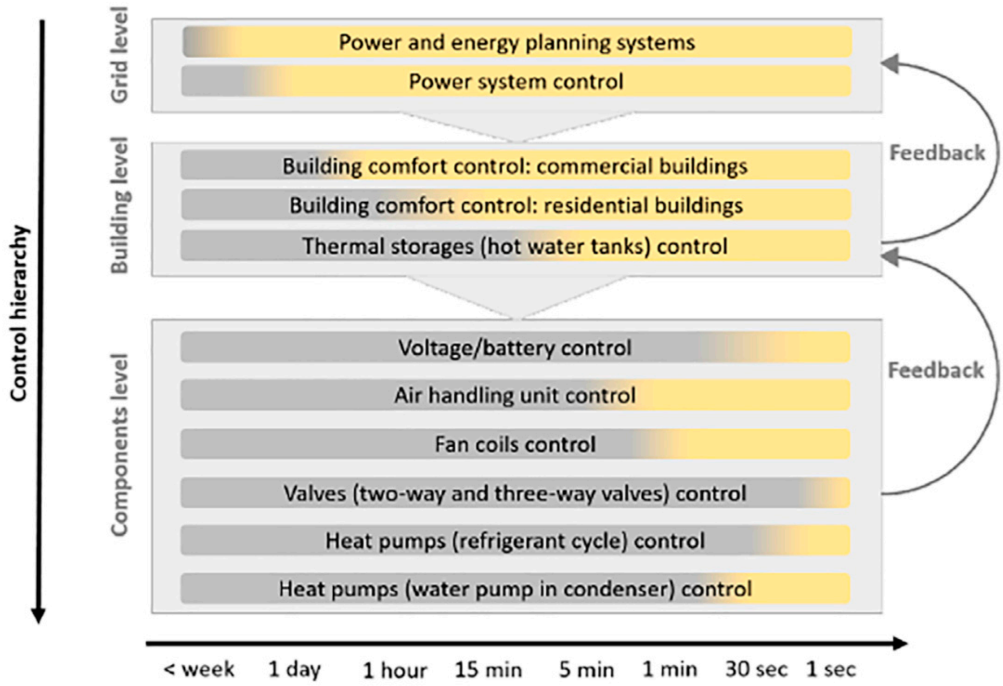

Figure 15. Illustration of control hierarchy and levels of integration [136].

An experimental architecture was proposed in [137], aimed to enable smart buildings by integrating HVAC systems with the grid. A bi-level optimization approach for integrating commercial buildings with a distribution grid was presented in [138]. It can reduce building operating costs while maintaining thermal comfort for occupants. For smart homes, a strategy including integration of renewable energy systems and scheduling and arranging the power flow during peak and off-peak periods was studied in [139]. More commonly, intelligent methods, including neural networks [140], linear programming [141], and differential evolution [142], have been used to optimize energy interactions for grid stress reduction.

In addition to the integration with the bulk grid, building energy management strategies have also been established for microgrids [143–145]. A management strategy for battery energy storage was proposed for commercial building microgrids, considering the operational costs and grid resilience. This strategy was able to increase the microgrid's resilience while maintaining the operational cost at a low level [143]. A framework for smart transactive energy in residential microgrids was proposed in [144]. An existing home-microgrid coalition formation scenario was used to verify the viability of the proposed method. Based on the work in [144], an enhanced transactive energy framework was further created to enable multiple residential microgrids to cooperate with each other by forming alliances in order to increase competitiveness [145]. In [146], the supply of regulation services by smart buildings was examined. Price signals were exchanged between the grid and building operators to adjust building energy usage. Additional research on buildings-to-grid (B2G) integration showed that HVAC control in grid-aware buildings can provide frequency management or ancillary services to the grid while maintaining occupants' thermal comfort to an adequate level. In [147], the control actions of both the power grid and buildings were coupled to optimize the performance. An MPC-based algorithm was developed to formulate the B2G integration, accounting for the time-scale discrepancy. To solve the duck-curve challenges by reducing the load-ramp rate, a predictive bidirectional control framework was presented in [138] for power flow control of B2G systems. Mirakhorli et al. [148] proposed a unique load aggregation method that used model predictive controlled loads and integrated power generation, grid constraints, and human behavior in a large cluster of buildings. The proposed method improved the control over multiple appliances and storage systems by introducing a behavior-driven price-based MPC for residential building energy management systems. Extensive testing on a large distribution network showed significant reductions in nodal voltage drop and peak loads with a 21% reduction in generation costs. Fan et al. [149] proposed a collaborative control optimization approach, as shown in Figure 16, for grid-connected NZEBs to improve their performance at the building group level. This approach used a game theoretic framework to coordinate the control of multiple NZEBs in order to maximize their overall performance. The results showed that the proposed approach can reduce peak demand, improve grid stability, and increase the utilization of renewable energy sources. Clastres et al. [150] proposed a mathematical model for optimizing the operation of a domestic PV system to provide ancillary services to the electricity grid. The model considered the intermittent nature of solar generation, the cost of electricity, and the value of ancillary services. It was found that PV systems can provide significant ancillary services to the grid, such as frequency regulation and voltage control. This could lead to increased reliability of the grid, reduced need for conventional generators, and lower electricity prices.

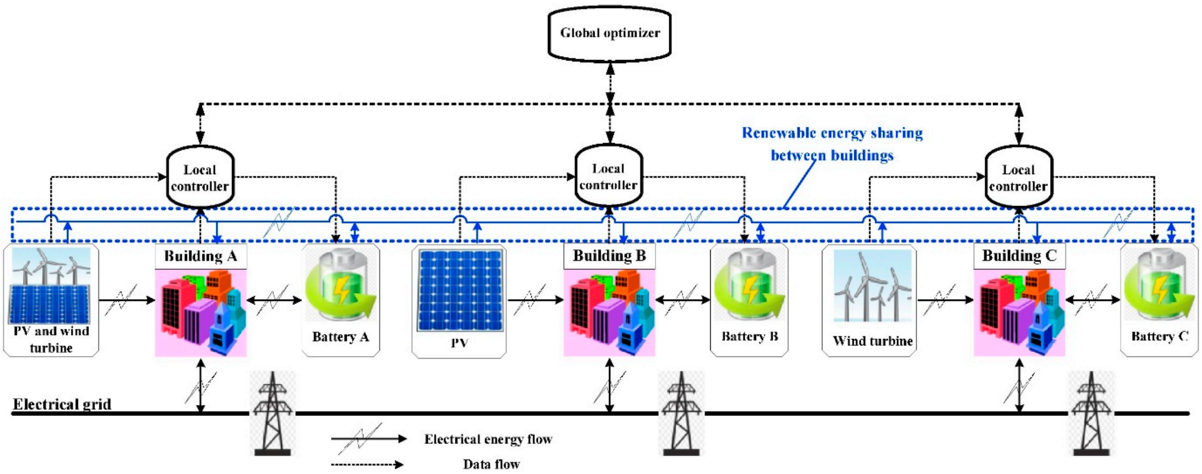

Figure 16. Illustration of a collaborative control approach [149].

Overall, these studies demonstrated the need for grid-integrated control for optimal demand response of buildings. Such control will be a critical aspect to support grid operation through the utilization of building integrated distributed energy sources. Further research is still needed to fully explore the benefits of grid-integrated control of buildings.

5. Conclusions, Future Direction, and Barriers

This paper provided a review of several emerging and sustainable technologies that can help achieve increased energy savings and reduced carbon emissions from buildings. These technologies ranged from onsite energy generation, thermal energy storage, heat pumps, and thermal energy sharing to advanced building design, retrofits, and data-driven modeling as well as improved building control and grid-buildings integrated control. Each technology showcased the potential to improve operating efficiency and increase demand flexibility to significantly reduce building energy consumption and carbon emissions while supporting grid operation.

However, how to rationally select technology combinations to achieve low energy operation is one of the key challenges during the design stage as this process is highly impacted by factors such as available budget, design objectives, and technological complexity. The uncertainty-based design has been considered in recent studies and has demonstrated its advances in improved robustness and increased resilience of the designed systems for buildings if circular economy principles are also considered during the design stage. To achieve building decarbonization, renewable energy and storage technologies are among the main solutions that are often considered, and they can potentially help take buildings off the grid. As a significant amount of electricity used in buildings is for heating and cooling, thermal energy recovery and energy sharing will play a key role in the development of smart communities and smart cities. Heat pumps will continue to be the main technology to provide heating and cooling to buildings in the coming decades. Research on the appropriate integration of heat pumps with renewable energy systems and energy storage technologies is needed.

For a particular application, the selection of appropriate energy technologies is quite complex, subject to the impact of many factors such as technology maturity, market availability, interoperability, scalability, applicability, long-term viability, and carbon reduction and energy reduction potential. A detailed cost-benefit analysis is often desirable to assess the short and long-term economic, social, and environmental impacts, enabling businesses and policymakers to make informed decisions. However, there often lacks sufficient historical data for sustainable energy technologies, making it challenging to estimate their future costs and benefits accurately. Moreover, the rapid development of technological advancements can make cost-benefit analyses quickly outdated, necessitating regular technology reviews and updates to ensure analyses remain reflective of the latest advancements and economic conditions. Hence, such analyses should also emphasize advanced location-specific assessments that consider regional variations in energy costs, incentives, and climate conditions. Expanding analyses to include life-cycle assessments can help assess the full environmental impact of technologies, including manufacturing, transportation, and disposal, enabling the identification of more sustainable options and leading to a circular economy.

On the technological side, exploring integrated technological solutions and models, in which multiple technologies can work synergistically to maximize their energy savings and carbon reduction, presents an exciting direction for research and implementation. However, the diversity of building types, sizes, and locations requires adaptable models to overcome these variations and provide generic assessments. High upfront costs associated with technologies like energy-efficient retrofits can impact their adoption and deployment, and thus, innovative financing models will be vital in lowering these initial investment barriers. Furthermore, proactive maintenance and monitoring strategies are required to optimize the system to ensure the long-term cost-effectiveness of these technologies.

To maximize the benefits of using these emerging and sustainable technologies in buildings, appropriate control, including building-level control and grid-buildings integrated control, is needed. Such control should have embedded intelligence and can enable the seamless optimization of building energy systems for increased demand flexibility and reduced operating costs while, at the same time, supporting flexible grid services with increased resilience. With massive data readily available from buildings, data-driven prediction and data-driven control will offer new opportunities to develop more advanced control solutions. Moreover, reinforcement learning and model predictive control can optimize building energy consumption through adaptive learning and near-optimal prediction, respectively. A combination of both controllers with embedded intelligence can enable buildings to continually learn, adapt, and operate in an energy-efficient manner. Grid-integrated control of buildings is predicted to be one of the leading solutions to support renewable energy-powered grids.

While numerous advancements have been made in recent years, ongoing research and development efforts remain crucial to improve the performance and effectiveness of these emerging and sustainable technologies and unlock their full potential in practical applications. The scalability and affordability of these technologies must be considered to ensure that they are accessible to a diverse range of building types and climatic conditions worldwide. In summary, by embracing and actively integrating these emerging and sustainable technologies into building design and operation, grid-responsive net zero energy buildings can be achieved.

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