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Review

A Comprehensive Review on Technologies for Achieving Zero-Energy Buildings

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Abstract: The booming of the building industry has led to a sharp increase in energy consumption. The advancement of zero-energy buildings (ZEBs) is of great significance in mitigating climate change, improving energy efficiency, and thus realizing sustainable development of buildings. This paper reviews the recent progress of key technologies utilized in ZEBs, including energy-efficient measures (EEMs), renewable energy technologies (RETs), and building energy management system (BEMS), aiming to provide reference and support of the wider implementation of ZEBs. EEMs can reduce energy demand by optimizing the envelope design, phase change materials integration, efficient HVAC systems, and user behavior. The renewable energy sources discussed here are solar, biomass, wind, and geothermal energy, including distributed energy systems introduced to integrated various renewable resources and meet users' demand. This study focuses on the application of building energy management in ZEBs, including energy use control, fault detection and diagnosis, and management optimization. The recent development of these three technologies mainly focuses on the combination with artificial intelligence (AI). In addition, this paper also emphasizes possible future research works about user behavior and zero-energy communities to improve the energy efficiency from a more complicated perspective.

Keywords: zero-energy buildings; energy-efficient measures; renewable energy technology; building energy management

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1. Introduction

The building industry is a critical area of focus due to its significant contributions to global energy consumption and greenhouse gas emissions, which consumes approximately 40% of total global energy [1]. Zero-energy buildings (ZEBs) have emerged as a pivotal strategy to reduce fossil fuel consumption and mitigate climate change. The primary objective of ZEBs is to minimize and even eliminate carbon emissions through the low-carbon transformation of traditional building materials, structures, and construction methods as well as through the optimization of conventional energy systems and management practices. To address the pressing challenges of climate change, reducing carbon emissions from buildings to zero or near-zero levels has become imperative [2]. This concept of ZEBs has garnered widespread attention and support, and it has become a cornerstone in the advancement of sustainable building practices.

In efforts to reduce fossil energy consumption in the building sector, different regions have established their own energy conservation and emission reduction targets. These regions are accelerating the implementation of ZEBs through the integrated application of various technologies, including carbon-saving measures in building mass and the adoption of renewable energy sources [3]. The United States has mandated that ZEBs must be technically and economically feasible between 2020 and 2030 [4]. Similarly, South Korea has set a roadmap for the adoption of mandatory ZEBs in the non-public sector by 2030 [5]. Researchers have developed a series of standards for achieving ZEBs. The German "passive house" model reduces building heating demand to 15 kWh/(m^2·a) by enhancing the thermal performance and airtightness of building envelopes, coupled with the utilization of high efficiency heat recovery system [6]. This approach represents a technical pathway towards achieving near-zero energy consumption. In November 2015, the Ministry of Housing and Urban-Rural Development of China officially released the standard "Passive Ultra-Low Energy Consumption Green Building Technical Guidelines (Residential Buildings)". Passive ultra-low energy consumption green buildings are defined as structures that achieve minimal energy consumption and a comfortable indoor environment by enhancing the thermal performance and airtightness of the envelope as well as by fully utilizing renewable energy technologies and high-efficiency air heat recovery systems [4]. These ultra-low energy buildings are considered as a primary form of nearly-zero-energy buildings. Consequently, the technologies used in ultra-low energy buildings can serve as the foundation for the development of a comprehensive ZEBs technology system.

Energy consumption during building operations includes the following aspects: heating, ventilation, air conditioning, lighting, domestic hot water, elevators, electrical outlets, cooking, etc. [7]. An optimized building structure coupling with an efficient building energy management system can be introduced to achieve building energy balance [8,9]. Researchers have summarized that the key methods implemented in ZEBs consist of two strategies: first, passive design such as an optimized building envelope design to minimize building energy demand, and second, active design, which involves the use of renewable energy technologies, including building-integrated photovoltaics, geothermal heat pumps, and photovoltaic direct-current systems to meet residual energy demands [10–13]. Among these, the adoption of renewable energy technologies (RETs) plays a central role in advancing ZEBs [14]. RETs can be the supplement of energy supply and cover the portion of energy use that cannot be reduced, thus reducing overall building energy demand. With further research in NEBs, building energy management and usage have emerged as a third category of innovative approaches to advancing ZEBs. In future scenarios, building energy systems, material recycling, and intelligent management will be integrated to maximize environmental, economic, and social benefits in NEBs.

This paper aims to review the technology system required in ZEBs. Sections 3 and 4 summarize the energy-efficient measures (EEMs) and RETs essential to ZEBs. Section 5 focuses on the application of building energy management systems (BEMS) in ZEBs. The research framework of these technologies is demonstrated in Figure A1. The future scenario for ZEBs is analyzed in Section 6, and the final section concludes the paper. Overall, this paper provides a necessary reference for advancing the development and enhancement of technology systems in ZEBs.

2. Development of ZEBs

This section summarizes and analyzes the existing world of ZEB research. Firstly, data were collected from a literature search in the databases of Web of Science, Scopus, and EI from 2013–2023 using the term "zero NEAR/0 energy NEAR/0 buildings". There were 1646 records gathered, comprising 1501 articles and 145 reviews, after excluding invalid literature types, such as proceeding papers, editorial materials, letters, and meeting abstracts. Figure 1 shows the increasing number of publications on ZEBs within the past ten years. Although the dataset does not cover all the years since the concept of ZEB has been put forward, the result has strongly reflected the impressive increase in efforts in ZEBs. It can be observed in Figure 1 that even though there was an advancement in publications between 2013 to 2016, the total number of articles was still modest. This period has been identified as the expansion stage of ZEB construction. Since 2019, the number of papers published each year has risen dramatically, reaching over 600 in Scopus. During this period, the researchers across the world put a high value on ZEBs, beginning the evident era of ZEBs. There are mainly two aspects mentioned as possible explanations for this occurrence.

Firstly, there was a significant advancement after several years of development. Secondly, the explicit concept of ZEBs and their methodologies still need to be improved, which in turn inspires further research in ZEBs [15]. This development trend is likely to continue due to global attention to sustainability.

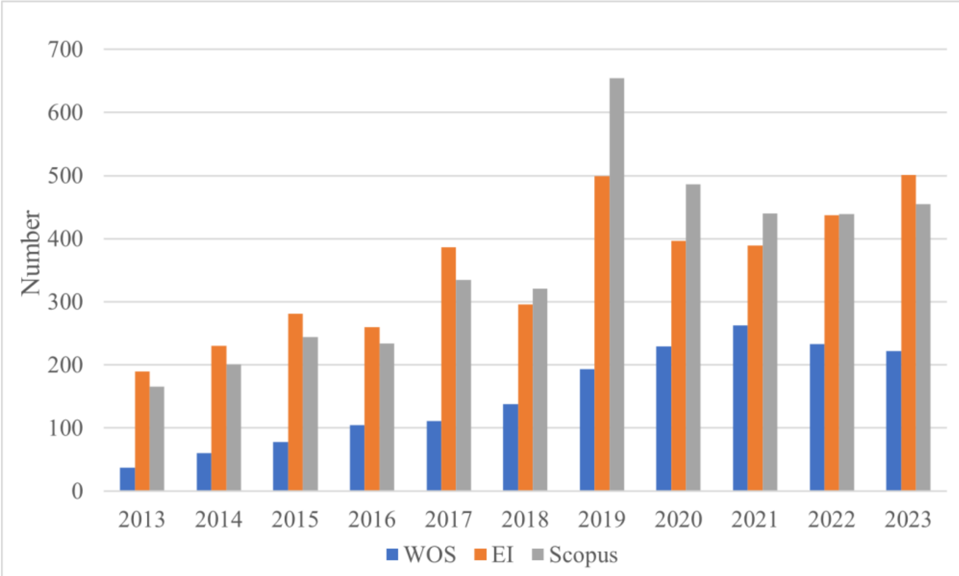

Figure 1. Amount of literature on ZEBs in different databases in 2013–2023.

The further analysis of spatial distribution of ZEB research countries revealed that China published the largest number of papers during 2013–2023, followed by Italy with 277 and Spain with 161. The results indicate that the scholars in China, Italy, and Spain are paying more attention to ZEBs. The top 20 countries with ZEBs research are listed in Table 1.

Table 1. Top 20 countries with ZEBs research in 2013–2023.

Order	Country	Number	Order	Country	Number
1	China	327	11	Finland	56
2	Italy	277	12	Australia	51
3	Spain	161	13	Belgium	51
4	USA	137	14	Germany	48
5	Republic of Korea	99	15	Poland	44
6	UK	76	16	Norway	43
7	Canada	73	17	France	40
8	Iran	63	18	India	39
9	Greece	61	19	Egypt	37
10	Portugal	61	20	Denmark	35

The density visualization of keywords in every paper on ZEBs from 2013 to 2023 is represented in Figure 2. The size of the keyword and the font weight correspond to the frequency of occurrence. It is shown that the term "performance" has the largest size and a relatively thicker font, which means the final performance of ZEBs after adopting various technologies attracted the most attention from researchers.

Meanwhile, the top 20 high-frequency keywords are shown in Table 2, and performance, design, system, optimization, and residential building are the top five terms that can be seen in Figure 2. The terms "performance" followed by "design" and "system" demonstrate that scholars have focused on the structure design and whole system in ZEBs, and both of these two aspects are closely related to the performance of the buildings. The term "optimization" also ranks highly, which means that researchers pay close attention to the optimization route of technology combinations used for ZEBs. The research on the design, construction, and optimization for achieving ZEBs is more based on residential buildings, but the research on ZEBs in office buildings is also increasing. Table 2 demonstrates that the term "office buildings" is also among the top 20 high-frequency keywords.

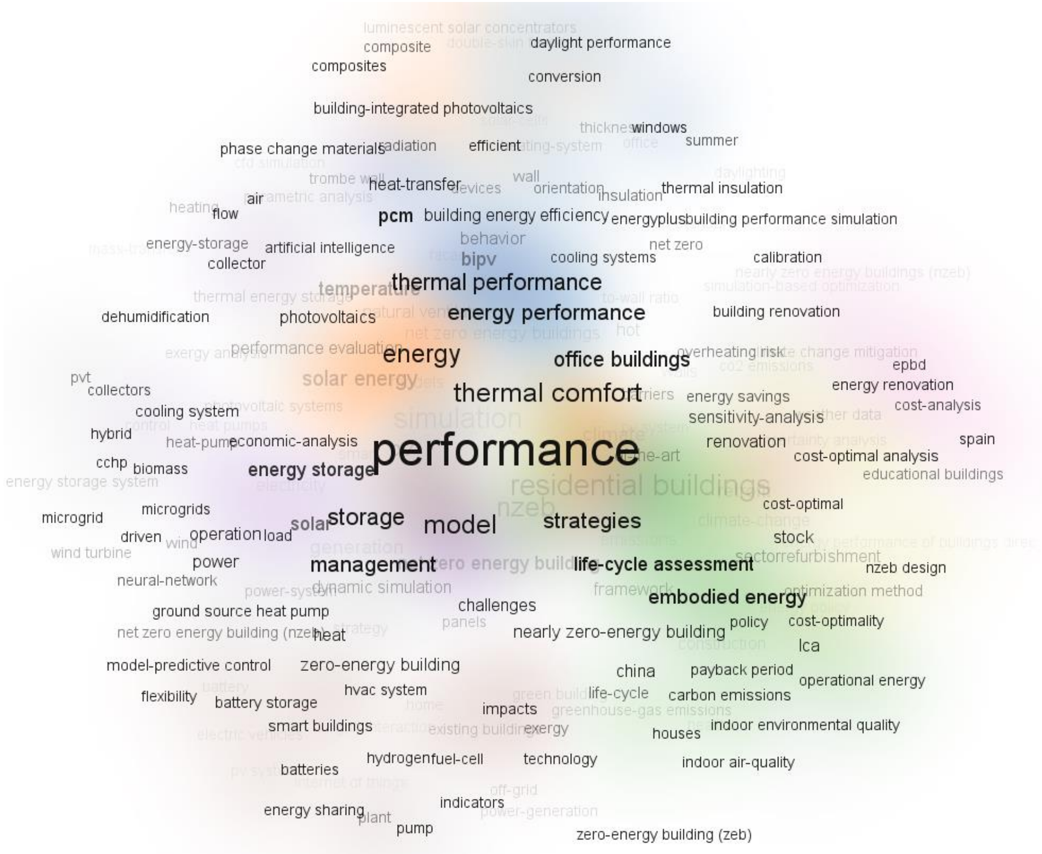

Figure 2. Density visualization of ZEBs research in 2013–2023.

Table 2. Top 20 high-frequency keywords in ZEBs research in 2013–2023.

Order	Keywords	Number	Order	Keywords	Number
1	performance	492	11	impact	118
2	design	324	12	buildings	112
3	system	318	13	storage	80
4	optimization	234	14	technologies	74
5	residential buildings	165	15	management	72
6	consumption	163	16	multi-objective optimization	71
7	efficiency	153	17	thermal comfort	68
8	simulation	149	18	cost	66
9	zero-energy buildings	140	19	strategies	63
10	model	123	20	office buildings	62

EEMs, RETs, and BEMS are the three main technologies for achieving ZEBs. Therefore, the development trend of these three technologies is analyzed in this section to clarify the most applied methods and the latest development trends included in EEMs, RETs, and BEMS.

Figure 3 illustrates the result of keyword co-occurrence of EEMs in *Vos viewer*. It highlights the emerging themes and time–domain shifts in research directions within the field of EEMs for ZEBs with smart technologies. This shows that researchers have primarily focused on finding pathways to achieve zero energy consumption in "dwellings" from the perspective of EEMs, with "windows" being the commonly studied part of building envelope before 2018. In 2019 and 2020, the thermal insulation of walls in the design stage was considered essential for achieving ZEBs, and multi-objective optimization was the common method. Since 2021, "phase change materials", "natural ventilation", and "heat pumps" have been the newest technologies for improving the energy efficiency. During this period, office buildings and commercial buildings have also been researched as the other building types for ZEBs. Figure 3 indicates that renewable energy and management should be coupled with EEMs for realizing net-zero energy consumption in multiple types of buildings.

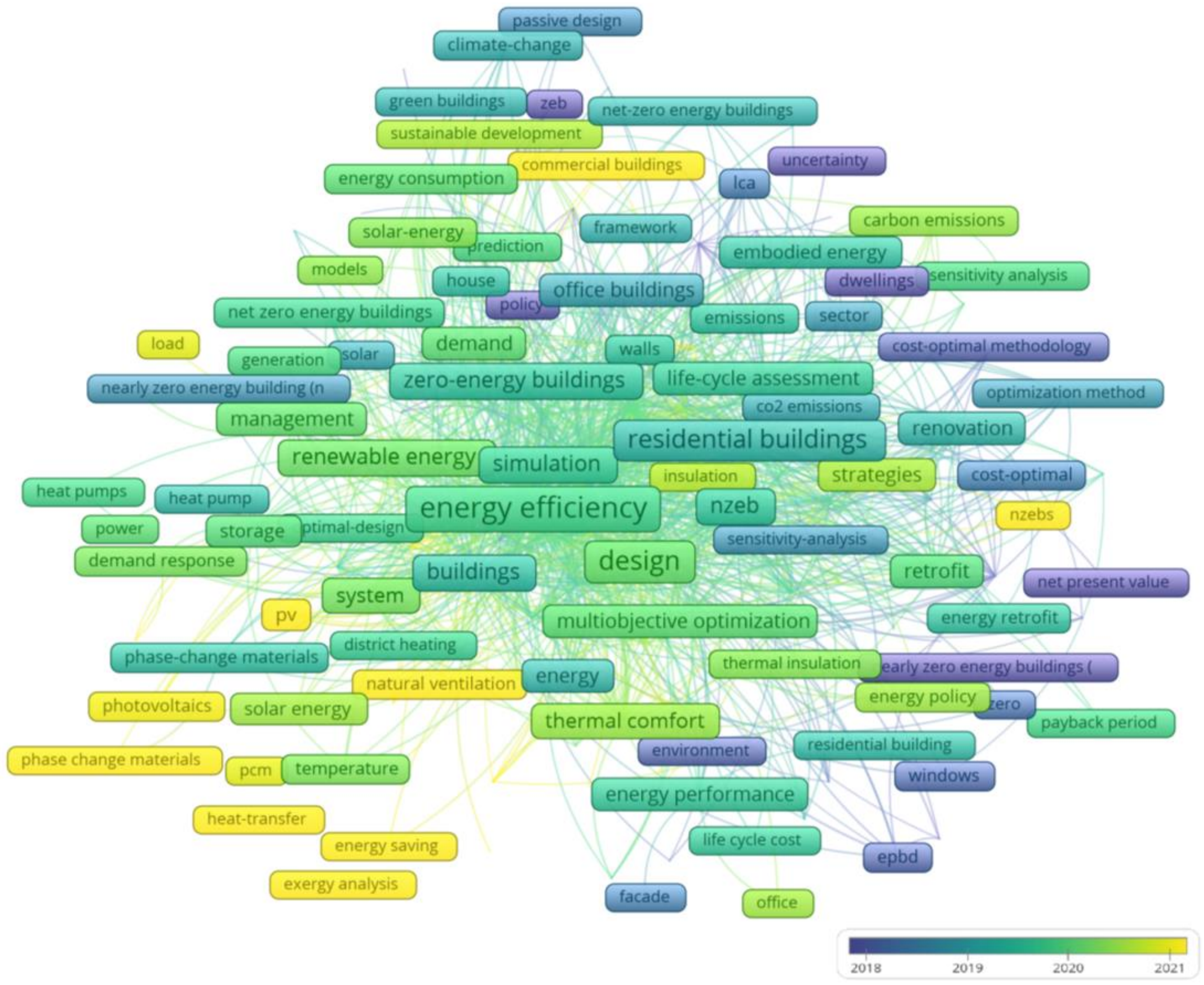

Figure 3. The trend of keyword co-occurrence of EEMs in ZEBs research from 2017 to 2022.

The development trend of the technologies included in RETs from 2017 to 2022 is represented in Figure 4. Solar energy was introduced early as a key technology, as it is a renewable source. Building-integrated photovoltaic and photovoltaic thermal energies are more mature methods applied in ZEBs at present. Nowadays, wind power and biomass are also attracting the attention of researchers for further development. With the research scope expanding from buildings to communities, electric vehicles have been added into whole-energy systems, and smart grids are being designed for better energy storage and transmission.

Figure 4. The trend of keyword co-occurrence of RETs in ZEBs research from 2018–2021.

Figure 5 illustrates the result of the keyword co-occurrence of BEMS in ZEBs research from 2019 to 2021. This shows that researchers have primarily focused on finding pathways to manage the building energy system from the demand side. This method pays more attention to the consumer of energy in buildings. With the integration of renewable energy into the entire zero-energy building system, the building itself is not only an energy producer but also a consumer, so the relationship between the components of the system is relatively more complex. Therefore, the strategies for control of the energy systems are comprehensive and need to be updated. Predictive control is helpful for evaluating the energy flow in the system in time and giving feedback to issue appropriate energy consumption instructions. During the control procedure, the complexity of the system can be imagined, which must involve a large amount of data storage, processing, and computing. Artificial intelligence (AI) and big data technologies have significant advantages in these aspects due to their higher calculation speed and accuracy, which can provide a scientific reference for the building control system. From the research, it can be seen that since 2021, AI has been widely used for high energy flexibility.

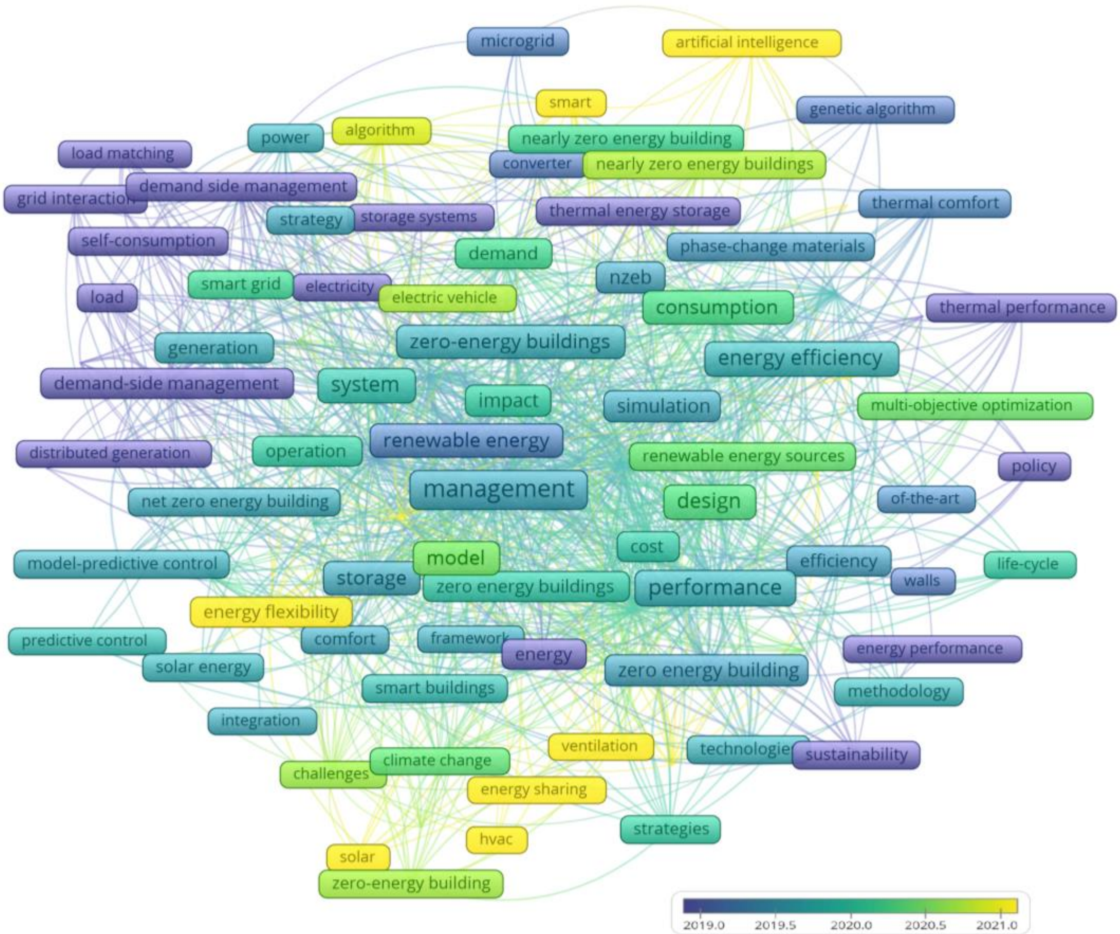

Figure 5. The trend of keyword co-occurrence of BEMS in ZEBs research from 2019 to 2021.

3. Energy-Efficient Measures

EEMs encompass a wide array of strategies aimed at reducing the energy demand in buildings during their design, construction, operation, and maintenance phases. EEMs are crucial in lowering operational costs, enhancing energy efficiency, and minimizing environmental impacts [13,16]. The implementation of EEMs is both essential and primary to prompt ZEBs. The EEMs in ZEBs include an optimized building envelope; the application of phase-change materials (PCM), which aim to reduce thermal loads; and efficient heating, ventilation, and air conditioning (HVAC) as well as occupant behavior, which focused on improving the energy efficiency of electric systems. Specifically, Table 3 exhibits the EEMs utilized in some national ZEB projects. High-performance envelope designs or the retrofitting of the building envelope are universally adopted; then, passive shading and ventilation are also utilized. Methodologies like high-efficiency HVAC systems, energy-efficient materials, and occupant control of the equipment are also widely used.

Table 3. Summary of EEMs applied in some international ZEB cases.

Building Type	Ref.	Energy-Efficient Measures
Residential	[17]	Envelope thermal resistance R-value, air–water-source heat pump, exterior wall retrofit, and windows/doors retrofit
	[18]	Building distance, urban grid's orientation, and window to wall ratio (WWR)
	[19,20]	Roof insulation, windows replacement, exterior walls insulation, ground floor insulation, doors replacement, heat recovery ventilation, and the building shape, orientation, and WWR
	[21]	Building orientation, windows type, WWR, and wall and roof insulation
	[22]	Thermal insulation materials, additional sunspaces, and phase-change materials

Table 3. *Cont.*

Building Type	Ref.	Energy-Efficient Measures
Office	[23]	Building orientation, window to wall surface ratio, U values of building envelope components, cooling set point, natural ventilation strategy, and shading systems
	[24]	Temperature setpoints, daylighting sensors, a low-emissivity glass, and upgraded HVAC systems
	[25]	U values of the building envelope components, the external shading, and the type and the upper limit of the ventilation airflow rate
	[26]	U values of the building envelope components, LED lighting systems, and VRV heat pumps
	[27]	U values of the building envelope components, window insulation, shading, and HVAC system

3.1. Improved Building Envelope

The energy efficiency of a building is largely determined by the thermal performance of its envelope, which also plays a critical role in ensuring indoor comfort and health [28]. Therefore, it is a primary and critical step to improve the building envelope's performance towards advancing ZEBs [29]. The building envelope comprises both opaque (such as facades, roofs, and floors) and transparent parts (such as windows and skylights). Key measures to enhance the performance of the envelope include improving thermal insulation and installing high-performance windows and good airtightness, all of which contribute to reducing heat loss and, consequently, the thermal load of buildings [30].

One of the primary measures is retrofitting walls in ZEBs. Generally, the lower the heat transfer coefficient, the lower the annual heating and cooling energy consumption. However, when the insulation capacity of the building envelope exceeds a certain threshold, the reduction in indoor heat loss can lead to increased cooling energy consumption, ultimately raising overall energy demand. Therefore, in regions where heating dominates annual energy consumption, improving the thermal insulation of the envelope is essential to minimize heating demand. Conversely, in regions where air conditioning is prevalent, enhancing envelope insulation may increase cooling demand, thereby diminishing its energy efficiency [31].

For transparent envelopes, the heat transfer coefficient (U), solar heat gain coefficient (SHGC), and WWR have significant influence on building energy consumption [32]. Studies have shown that heating and cooling demand is minimized when the U value is below 0.8 $W/(m^2 \cdot K)$ and when the SHGC ranges between 0.2 and 0.6, which is favorable for building energy conservation [30]. Zhang et al. [33] conducted a sensitivity analysis of building envelope parameters using a parametric model, concluding that the U value of a window is second only to the U value of an external wall in its impact on building energy consumption, while the WWR has a weaker effect compared to the building envelope. Moreover, due to the influence of orientation, there are differences in the value of WWR between south and north directions. Nonetheless, buildings with WWRs ranging from 0.30 to 0.45 generally exhibit relatively low energy consumption across different climatic zones and orientations [34].

In the field of energy-efficiency measures, a large number of studies have optimized sunlight performance by using different algorithms to optimize parameters such as window to wall ratio, orientation, and building layout [35,36] for reducing building energy consumption. There are also studies that have used optimization models and AI optimization algorithms (such as NSGA II, DSE, and MOPSO) to integrate machine learning prediction models into evaluation functions during the evolutionary process, effectively searching for Pareto optimal building envelope solutions [37]. Razmi et al. [38] used PCA-ANN integrated with NSGA-III to design the optimal design scheme for dormitory buildings to improve energy efficiency, sunlight, and thermal comfort. Ciardiello et al. [39] developed a multi-objective and multi-stage NSGA-II optimization framework to optimize the energy performance of newly constructed residential buildings in the Mediterranean climate. In the first stage, geometric features, including shape, shape ratio, window to wall ratio, and orientation, are optimized to minimize heating, cooling, and total energy demand. Then, the occupant behavior and management strategies can be considered to be a constraint to optimize the design and retrofit of the building envelope in future research.

3.2. Phase-Change Material Integration

The integration of PCMs into the building envelope has emerged as a prominent research field in recent years. PCMs are characterized by high storage density and minimal temperature fluctuation. They utilize natural temperature differences as the driving force for phase-change processes, facilitating heat absorption and release, which could effectively harness solar energy. PCMs can increase the heat capacity of the envelope and reduce indoor air temperature fluctuations, thereby enhancing indoor thermal comfort. On the other side, PCMs help balance the timing and intensity of energy supply and smooth the power output, effectively shaving peaks and filling valleys [40]. PCMs can be incorporated into various parts of building envelope, including walls, windows, roofs, and floors. Research has shown that the integration of PCMs can reduce heating energy consumption by 17.5% in dry climates and 10.4% in semi-arid climates while also increasing indoor thermal comfort satisfaction from 63% to 75% in semi-arid climates and from 73% to 93% in dry climates [41]. Kalbasi et al. [42] compared the thermal performance of common insulation materials and PCMs across different climatic conditions, finding that PCMs outperform insulation materials in summer, while insulation materials are more effective in winter. However, the effectiveness of PCMs is influenced not only by climatic conditions but also by the thickness of the material and its installation location. Al-Yasiri et al. [43] suggested that in hot climates, PCMs should be installed near the exterior of the building envelope to prevent heat from being emitted indoors, whereas in cold climates, PCMs should be located closer to the interior of the envelope. Therefore, further research is needed to enhance the sustainability of PCMs under varying climatic conditions and to explore the potential of composite phase-change materials in combination with other materials to enhance its suitability and then improve the building energy efficiency.

In addition, K. Bhamare et al. [44] developed a thermal performance prediction model for PCMs-integrated roof buildings based on machine learning and deep learning, taking into account the changes in thermal and physical properties of phase-change materials and proposing a new indicator, the Key Response Measurement (MKR) index, to evaluate the performance of PCM-integrated roofs. Hai et al. [45] proposed a method using the ANN algorithm to predict building energy consumption at different installation positions of phase-change materials under fixed wall thickness. The above research indicates that intelligent technology has strong application prospects in achieving the applicability of measures to improve building energy efficiency with zero energy consumption. Whether in the early design stage or later renovation stage, intelligent technology can provide a certain scientific basis for design and renovation of ZEBs based on a large amount of data.

3.3. HVAC Systems

HVAC systems and electrical lighting account for 40–60% and 20–30% of total energy consumption, respectively [46]. Improving the efficiency of these electric systems plays a crucial role in ZEBs. Thermostats regulate the HVAC system by setting and adjusting indoor temperatures, and proper thermostat set point can significantly reduce cooling and heating loads while maintaining indoor thermal comfort. For instance, a study conducted in Las Vegas demonstrated that increasing the thermostat temperature by 2.2 °C between 4 and 7 p.m. during summer can reduce peak energy consumption by 69% [47].

There are mainly two methods to maximize the efficiency of HVAC systems in ZEBs. Selecting the optimal device of the HVAC systems and selecting the best coordination among the various components are the relatively direct ways to realize this target. Papadopoulos et al. [48] developed a multi-objective optimization model to adjust HVAC temperature set points, aiming to minimize energy consumption while maximizing indoor thermal comfort. Various HVAC system alternatives, such as air-source heat pumps, ground-source heat pumps, heat recovery ventilation, and energy recovery ventilation, have been explored to improve energy efficiency. Wu et al. [49] compared the energy consumption in ZEBs with different ventilation, dehumidification, and heat pump options, revealing that heat recovery ventilators and energy recovery ventilators reduced HVAC energy consumption by 13.5% and 17.4%, respectively, and decreased overall building energy consumption by 7.5% and 9.7%, respectively. Furthermore, Kathiravel et al. [50] applied a Building Information Modeling (BIM)-based fuzzy approach to assess the performance of three types of HVAC systems under six different climatic conditions. The results indicated that air-source heat pump systems are the optimal choice in milder climates. Combining smart technologies with multi-objective optimization is a normal method nowadays to enhance energy efficiency without compromising the comfort of users. Moreover, there is other consequential method to improve the efficiency of HVAC systems. The use of energy-efficient lighting and high-efficiency electrical appliances (such as refrigerators, washing machines, and dryers) not only directly reduces electricity consumption but also decreases the cooling load of the HVAC system by emitting less heat. Implementing energy-efficient lighting with dimming controls and appropriate daylighting schemes can help reduce electricity demand, enhance visual comfort, and contribute to the development of ZEBs [51].

3.4. User Behaviors

Numerous studies have shown that the inclusion or exclusion of user behaviors in building energy simulations can lead to significant variations [52]. This issue is also critical for ZEBs, where even buildings in the same location can have varying energy consumption due to user behaviors. Smart technologies for capturing user behavior characteristics can reduce uncertainties and provide key variables for improving energy consumption prediction accuracy. Roy et al. [53] compared 14 machine learning models, such as linear discriminant analysis, SVM, and random forest, to detect the window-opening behavior of the occupants during the heating season. Abolhassani et al. [54] proposed that it was convenient to extract user behaviors according to the home Wi-Fi usage data. It was highlighted that Wi-Fi has great potential for large-scale urban applications due to its low cost and privacy protection. Kazmi et al. [55] developed a hybrid reinforcement learning strategy for domestic hot water usage patterns based on user behavior and an air-source heat pump thermodynamic model to improve energy use efficiency. Due to the uncertainty of user behaviors, it is particularly important to use intelligent technology to analyze users' control behaviors regarding equipment and devices and capture the rules.

Given the varying indoor comfort requirements among users, balancing energy costs and user comfort is a major focus in ZEBs. Missaoui et al. [56] investigated the performance of a global model-based anticipative building energy management system in managing household energy consumption. The researchers used a multi-objective optimization approach that considered total energy costs and user dissatisfaction as the objectives and user expectations and energy prices and power limits as the constraints. Forastiere et al. [57] used BIM to evaluate the energy performance of existing buildings and identify effective retrofitting measures for achieving ZEBs. In this case, indoor comfort, energy efficiency, CO2eq emission reduction, and the social cost of carbon were all considered to achieve optimization. Papadopoulos et al. [48] used the NSGA-II algorithm to adjust the set point of the HVAC, achieving nearly 60% annual energy savings without compromising the user's comfort in a moderate climate. There is a strong link between user behaviors and their indoor comfort. The pursuit of higher comfort is inevitably compromised by higher levels of energy consumption; therefore, the design of ZEBs must take user comfort into consideration.

4. Renewable Energy Technologies

Following the integration of the EEMs, the deployment of on-site RETs has become the subsequent focus, often representing the most cost-effective solution to minimize energy consumption and overall project costs [58,59]. RETs can convert natural resources into usable energy forms through technological means, while these energy forms can be recycled without depletion. Compared to traditional energy sources, renewable energy sources are more environmentally friendly, safe, and sustainable. Renewable energy sources such as solar, geothermal, wind, biomass, and air have become key strategies for advancing ZEBs and zero-energy communities (ZECs) [60]. Typical RETs include solar photovoltaic (PV) systems, ground-source heat pumps (GSHP), and wind turbines, which could be integrated into buildings, generating electricity and heat to achieve a net-zero-energy balance.

Among the various renewable energy sources, solar energy is particularly desirable due to its non-polluting nature, availability, and feasibility. The applications of solar energy are generally categorized into two forms: PV modules, which directly convert available solar energy into electricity, and solar photovoltaic thermal (PVT) modules, which convert solar energy into thermal energy and electricity [61]. Installing PV panels on rooftops can prevent indoor overheating while simultaneously generating electricity to meet part of the energy demand in buildings, making it one of the most effective methods in ZEBs [62].

PV systems have significant energy-saving potential, so they become the common method in ZEBs. Current research on PV systems primarily focuses on the thermoelectric property, energy-saving potential, and technical performance [63–65]. PV systems are typically installed on building roofs to maximize the energy absorbing from solar radiation. Due to this characteristic of PV modules, the impact of PV roofs on building loads and their thermal insulation effects have been extensively studied. As the PV module captures and utilizes incident solar energy, any unused energy accumulates as heat, which will increase the surface temperature of the module and reduce electrical efficiency [66]. The solar PVT system addresses this issue by using different kinds of working fluid, such as air and water. The working fluid can absorb the remaining solar energy accumulated in the PV module, which significantly improves electrical efficiency [61].

Depending on the different installation method, PV modules are classified into building-attached photovoltaic (BAPV) and building-integrated photovoltaic (BIPV) systems. In BAPV, PV systems are attached to the surface of building roofs, walls, and other structures that do not constitute the building envelope. Conversely, in BIPV, PV systems serve as a part of the building envelope, absorbing the solar radiation to generate electricity. BIPV not only saves building materials and hence reduces costs but also synchronizes with the design, construction, and installation procedure of the building [65]. BIPV represents an innovative approach to effectively integrating photovoltaic panels with buildings [66,67]. According to the geography of the construction site, climate conditions, building functions, and the surrounding environment, the building layout, orientation, spacing, grouping, and spatial environment are determined, and thereby, PV modules are integrated into the building. By installing solar PV panels on the exterior surface of the building envelope, BIPV can increase the power generation per unit of floor area and enhance the feasibility of using solar energy as a supplement or alternative to the grid [11].

In addition to solar energy, other renewable energy sources are widely utilized due to their unique advantages. For example, geothermal energy is more stable than other renewable sources, is unaffected by weather, and does not require storage equipment to manage fluctuations in electricity demand, providing a reliable and sustainable electricity solution for ZECs [68]. Although wind energy is more unstable, it is more environmentally friendly and particularly advantageous in specific climatic regions. Bioenergy, on the other hand, is unaffected by climatic conditions, and it can ensure a stable energy supply as long as there is an adequate supply of raw materials [60]. The various technological applications of these different renewable energy sources are summarized in Table 4.

Renewable energy technologies have an important role to play in the realization of ZEBs but have the significant drawback of high instability, with solar and wind energy being highly susceptible to meteorological conditions and fluctuating with solar radiation and wind speed. Geothermal energy, while more stable, requires a consistently good range of subsurface temperatures. In addition, when new energy sources are integrated into community distribution grids, their instability can lead to significant grid output fluctuations, which can seriously affect consumers' normal electricity consumption [75].

Table 4. Summary of renewable energy sources and their applications.

Energy Category	Applications
Geothermal energy	Geothermal energy is widely used for heating and cooling in a variety of buildings and transport areas [69]. Geothermal energy is used in GSHP systems as an energy source. GSHP systems typically consist of vertically drilled heat exchangers that are employed to extract heat from the ground [70].
Wind energy	Wind energy systems and wind farms are the main forms of wind energy utilization in carbon-neutral communities [71]. Due to the instability of wind energy, the integration of wind energy with other energy sources, such as solar, thermal, and electrical, is necessary to create sustainable energy systems.
Biomass energy	Biomass requires the conversion of biological sources such as wood waste and municipal waste to generate electricity, using biochemical methods such as pyrolysis, gasification, liquefaction, and combustion to provide electricity. Biomass energy is mainly used in heat and power systems, e.g., in combination with a GSHP [72].
Ocean energy	Ocean energy comes from waves, tides, currents, and heat that can be used to meet power-generation needs [73]. Ocean energy can be harvested from the oceans in four different ways: wind, tides, waves, and the temperature difference between deep and shallow oceans [74].

With regard to the lack of stability of the power supply from a single renewable energy source, Liu et al. [76] highlighted the critical importance of grid stability when integrating large-scale, fluctuating renewable energy sources with existing power infrastructure. To enhance energy efficiency and ensure the security and stability of the power system, most ZEBs now integrate multiple RETs. For example, the Hockerton Housing Project in the UK utilizes both PV and wind power-generation facilities to ensure sufficient electricity supply for the community [77]. Similarly, the Leaf House incorporates PV power generation, with heating demand and hot water load supplied by GSHPs, and there is an auxiliary gas-fired boiler to ensure a stable thermal energy supply [78]. Zhu et al. [60] proposed the establishment of an integrated renewable energy system to enable new energy sources to flexibly meet consumer demand through effective energy storage technologies [55].

As research on ZEB progresses, new approaches are being developed to address energy losses in the alternating current (AC)–direct current (DC) conversion process [79]. One such approach is the "photovoltaics, energy storage, direct current, and flexibility" system integrated into the building. This system employs distributed photovoltaics, energy storage devices, and DC power supply to transform the power system of the building from a rigid load to a flexible one, which can be adjusted according to the supply and demand relationship of the power grid [80]. By utilizing DC power supply, energy losses can be significantly reduced, and thus, the building energy efficiency can be improved.

A distributed energy system (DES) can be tailored flexibly according to the specific needs of users. Traditionally, DESs rely on natural gas as the primary energy source. However, it is helpful to use renewable energy sources as the primary input in ZEBs to achieve energy balance. Due to the fluctuating and intermittent nature of renewable energy sources like solar, geothermal, and tidal energy [81], it is necessary to combine energy storage technologies with a DES, which can enhance their sustainability by enabling peak shaving and valley filling. Studies [82,83] have indicated that a DES with energy storage can better reduce carbon dioxide emissions compared to those without the function of energy storage. Li et al. [84] developed a new DES that combined thermal storage modules with conventional DES components, including prime movers, absorption chillers (ABS), PV modules, and GSHP. Bartolini et al. [85] proposed a DES that integrated electric chillers, ABS, internal combustion engines, PV modules, and lithium batteries to meet the energy demands of residential and office buildings. Liu et al. [86] proposed a novel DES incorporating PVT modules, solar collectors, and hybrid energy storage (heat, ice, and electricity), achieving a 50% reduction in annual carbon emissions and improving system performance. Rocha et al. [87] used AI techniques to design a distributed electricity generation system with wind usage system, PV systems, battery packs, and automatic capacitor banks. This system met about 160.5% of the electricity demand of the building and 99.999% of annual energy costs, essentially achieving zero-energy status. Studies have demonstrated that DESs have promising applications regardless of the building type. When integrating with renewable energy sources, DESs not only realize cogeneration cooling heating and power but also reduce the energy consumption.

Although many studies have focused on the design and optimization of the DES, the limitation of application scenarios has been manifested. Clustering multiple ZEBs in the same area will demand higher overall performance from the DES. Kim et al. [88] applied a DES in a ZEC with various building types and evaluated its performance from environmental and economic perspectives. Liu et al. [89] proposed a DES integrating PV systems, hybrid energy storage, and energy loads of electric vehicles, using NSGA-II for multi-optimization in 12 different nearly-zero-energy community scenarios. In ZECs, it has been shown that there are multiple energy storage devices, multiple RETs, complex DES structures, and difficulties in optimization. Based on the above characteristics, Guo et al. [90] introduced a two-layer co-optimization method that considered the equipment configuration on the upper level and energy storage parameters on the lower level. The result showed better stability, accuracy, and reliability compared to multi-layer and two-stage methods.

Moreover, although RETs and solar, wind, biomass, and geothermal energy are the most commonly applied sources in ZEBs, due to the environment-dependent nature of renewable energy sources, their controllability and predictability are often limited [91]. Smart technologies offer effective solutions to overcome these limitations by accurately predicting energy fluctuations. Wu et al. [92] explored a multi-objective optimal design approach using the Grasshopper platform and NSGA-II to minimize HVAC energy consumption, maximize PV power generation, and minimize investment costs in ZEBs. In the research field of RETs in ZEBs, optimization of single renewable energy technology is less well studied and is usually dominated by solar PV systems.

Extending the concept of zero energy from the single-building scale to the community or city scale, electric vehicles (EVs) play a key role in achieving ZECs. However, the increased peak loads caused by EV charging pose technical challenges to the power system. Moreover, the introduction of energy equipment increases the complexity of the original energy system. Accordingly, it is a quite straight and quick method to use AI technologies while faced with a scenario with multi-systems and complex data. Fachrizal et al. [93] evaluated optimal city-scale energy-matching power in wind- and solar-powered net-zero-energy cities under different EV charging scenarios, finding that it had great potential to enhance energy system performance due to the flexibility of EVs. Gao et al. [94] proposed a genetic algorithm-based method to reduce overvoltage risk in ZEBs connected to the grid by adjusting the key parameters. The result showed that this method effectively mitigated grid overvoltage and decreased building energy consumption.

Energy is a critical factor influencing economic development, and innovation in RETs is at the core of the energy revolution [95]. In the face of the global energy crisis and climate change, the development and utilization of renewable energy sources and the research of new RETs are essential for reducing energy consumption in buildings and addressing global development issues. Different renewable technology options are available for different climatic locations and building codes, and building industry practitioners need to select technologies that meet local conditions and constraints. In addition, in the future, research needs to be strengthened regarding new renewable energy technologies and in support of energy storage and other technologies to reduce building energy consumption and enhance new energy stability and to explore the use of AI technologies to achieve control optimization and automated operation of the system in order to improve the efficiency of RETs and the stability of the grid.

5. Building Energy Management

EEMs and RETs provide a minimum threshold for achieving ZEBs from the perspective of energy demand and energy supply. Building Energy Management Systems (BEMSs) integrate energy-efficiency measures and renewable energy technologies through reasonable and effective control strategies to minimize energy costs and pollution and maximize the energy saving. BEMS is the conjunction of methods and techniques used to monitor and optimize the building energy supply and consumption, maximizing occupant thermal comfort and productivity. Common issues in building operations include a focus on construction over management and on design over commissioning, which lead to building energy efficiency falling short of design expectations [12]. The intelligence and simplicity of BEMS are therefore crucial for ZEBs. Accordingly, the intelligent BEMS has become a key measure for standardizing and achieving ZEBs.

There are two kinds of BEMS methods, namely active and passive, which are similar to the passive and active design in ZEBs. Passive methods are based on providing future strategies and improving the user's energy awareness to influence and decrease the utilization of energy in buildings indirectly. Active methods are based on the mix of actuators and sensors in the building to reduce the energy waste [96]. Passive methods are more likely to be realized by long-term education. Therefore, from a pure technical perspective, active approaches currently represent the most feasible method to achieve ZEBs. Based on active approaches, there are mainly three management strategies: energy usage control (EUC), fault detection and diagnosis (FDD), and management optimization (MO). The comparison among these three methods is shown in Table 5.

Table 5. Summary and comparison among three active approaches.

Management Strategy	Methods	Contributions	Limitations
EUC	Stopping the use of elevators and lighting during off-peak hours, standardizing indoor temperature settings at 26 °C in summer, and adjusting fresh air ventilation according to the number of occupants	Low-cost, more feasible to achieve energy-saving targets, the implementation process is relatively simple	Reduces occupant productivity and indoor environmental quality, leads to dissatisfaction and complaints, and decreases the overall service level of buildings [97]
FDD	Conducting diagnostics on equipment and system, performing preventive maintenance and early overhauls on high-energy-consuming equipment, and upgrading the equipment	Significant improvement in energy efficiency [98], lower operational cost, and improved system reliability	Substantial financial cost, incompatible with the existing systems, long investment payback period
MO	Optimizing equipment operation, matching energy supply and demand, and optimizing the building automation system	Flexibility and scalability, quick effectiveness, reduced energy equipment load	Relatively complex system, the dependency of AI

Effective and meticulous management during the operational phase is essential for achieving energy efficiency and realizing net-zero energy consumption. In recent years, building energy management has shifted from process management to target management of total energy consumption and energy intensity. With the integration of renewable energy sources, buildings not only consume but also produce energy, thus becoming both "producers" and "consumers". This shift necessitates active self-management that comprehensively considers the energy consumption capacity and economic issues of the buildings [97]. Existing BEMSs face limitations due to static set points for heating, cooling, and lighting as well as issues such as complex data, missing information, and network problems [99]. Consequently, there is a need for advancements in BEMSs. IoT and AI technologies are essential for providing significant support in modern BEMSs.

Integrating AI and the Internet of Things (IoT) will provide a feasible implementation path for advancing ZEBs through intelligent management and control of various building systems, such as building automation, intelligent lighting systems, and energy distribution systems. It has been shown that the IoT-based intelligent control system of central air conditioning can achieve annual energy savings up to 30% [13], demonstrating the significant role of intelligent BEMS in reducing building energy consumption and improving the energy efficiency.

In ZEBs, extensive research has been conducted to reduce energy consumption through efficient building energy management. A literature search was carried out in Web of Science using terms "Building Energy Management System" and "Building Energy Management System" AND "AI OR AI OR machine learning OR deep learning OR algorithm", respectively. The number of articles that resulted is shown in Figure 6, where there one can see the steady increase in published research articles on BEMSs from 2018 to 2023. Research on the intelligent technology in BEMSs shows the similar trend with BEMSs, which reflects the increasing integration of emerging technologies in BEMSs, with an overall upward trend in research focused on intelligent technology applications.

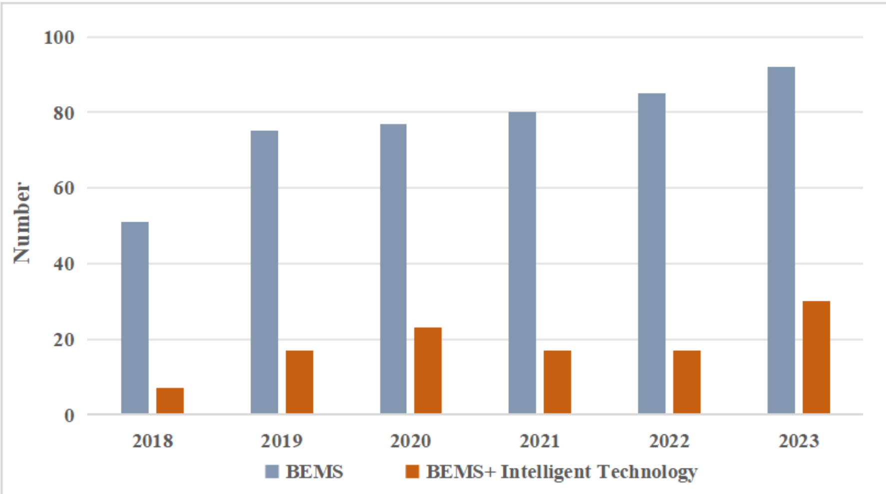

Figure 6. Number of published papers on building energy management in ZEBs from 2018 to 2023.

Figure 7 illustrates the result of the keyword co-occurrence in Vos viewer. It highlights the emerging themes and time–domain shifts in research directions within the field of intelligent BEMS for ZEBs with smart technologies. This shows that researchers have primarily focused on the demand-side management to achieve zero energy consumption in "residential buildings", with "genetic algorithms" being the most commonly employed method in 2022. As technologies have advanced, the focus has expanded to both building self-consumption and energy sharing to establish the load model by using "reinforcement learning", "deep learning", and so on. The change of research trends has shown that the renewable energy integrated into BEMSs introduced new energy consumption patterns, which included energy supply and energy consumption, therefore changing the conduct of the building from an unresponsive to a dynamic provider [100]. As for "reinforcement learning", it can be employed to continuously refine operational strategies through self-learning and accumulating operational experience. This method does not require a large amount of high-quality data for training. Instead, it follows a state–action–reward–state–action (SARSA) procedure to interact with the environment and make real-time decisions, which is particularly well suited for BEMSs nowadays [101].

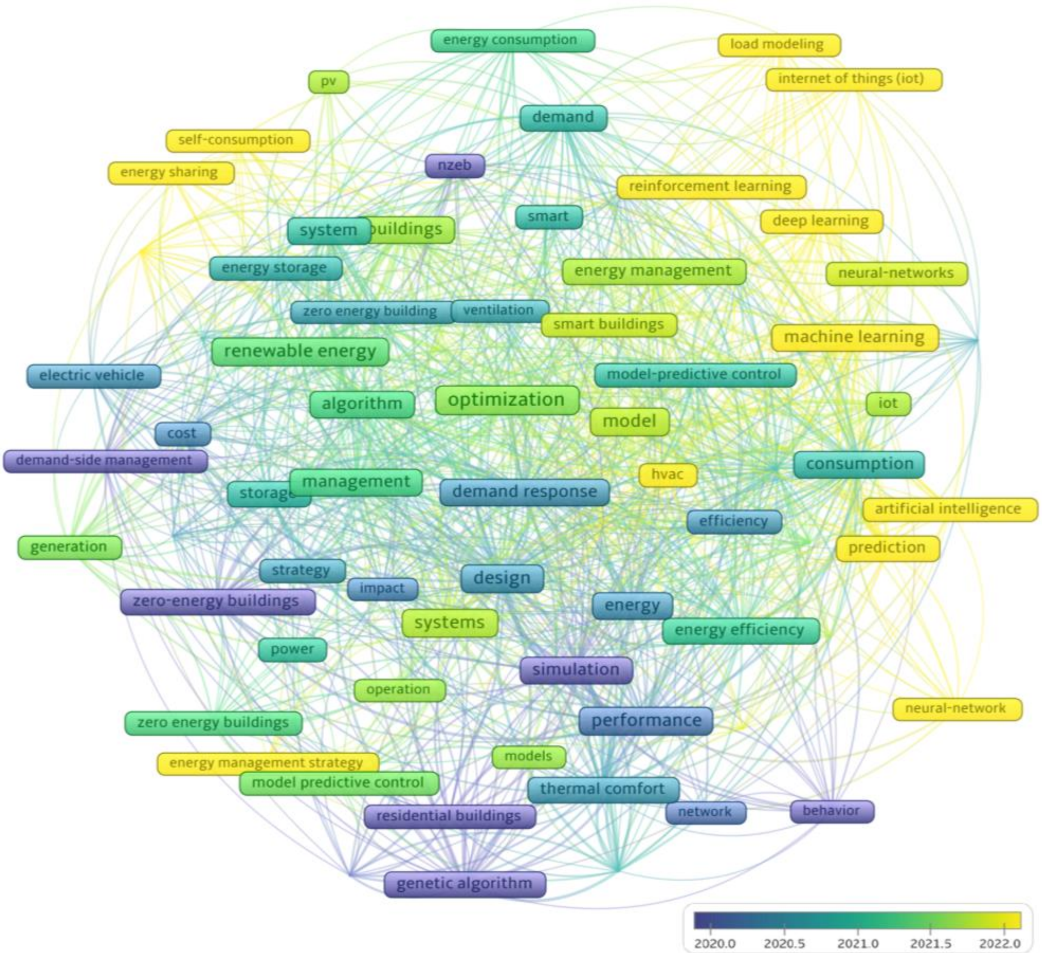

Figure 7. Keyword co-occurrence of intelligent BEMSs in ZEBs research from 2020 to 2023.

Based on the research tendency of BEMSs in ZEBs, there is great potential for intelligent technologies to be used in three active approaches. The categorization based on these three building energy management strategies using intelligent technologies is presented in Table 6.

The BEMS plays an important role in controlling electric devices such as HVAC and lighting systems in buildings. EUC in BEMSs focuses on the control patterns that meet the occupants' requirements of environmental comfort and energy saving. A large amount of physical environment data are used to train and test the energy use model. Control systems leveraging IoT and AI technologies can effectively capture environmental changes and then build prediction models so as to greatly improve the accuracy of the control system. Dynamic control of indoor temperature is a well-recognized method for optimizing the performance of HVAC systems and reducing building energy consumption. HVAC systems can be equipped with temperature sensors that can instantly adjust indoor thermal conditions to maintain occupant comfort. Various HVAC prediction models have been developed, including physical information-based models, data-driven models, and hybrid models. Data-driven models, also called "black box", which simulate thermal dynamics without explicitly defining specific thermal characteristics, are particularly suited for simulation purposes [116]. Machine learning algorithms such as support vector machine (SVM) [103,117], XGBoost [118,119], and artificial neural network [120] are commonly used for indoor temperature prediction. These approaches not only reduce costs but also enhance energy efficiency.

Table 6. Summary of research papers based on building typology, techniques, and management strategies.

Reference	Authors	Building Typology	Building Subsystem	Techniques	Management Strategies
[102]	Bagheri et al.	Office	HVAC	Control algorithm	EUC
[103]	Chen et al.	Commercial	HVAC	Hybrid SVM	EUC
[104]	Xu et al.	Office	HVAC	Long short-term memory	EUC
[105]	Faiz et al.	Experimentation room	HVAC	Transformer neural networks	EUC
[106]	G. Varghese et al.	Experimentation room	Lighting and window blinds	Wireless sensor actuator networked system	EUC
[107]	Shen et al.	Office	Lighting	Multi-object relative position detection algorithm	EUC
[108]	Kandasamy et al.	Experimentation room	Lighting	ANN	EUC
[109]	Sharif et al.	Office	HVAC and lighting	Simulation-based multi-objective optimization	FDD
[110]	Fang et al.	Office	HVAC	SVR	FDD
[111]	Han et al.	Unspecified	Centrifugal chiller	Least squares–support vector machine	FDD
[96]	Gaur et al.	House	Overall	Statistical approach, segmented linear regression	FDD
[112]	Qais et al.	Residential	Energy storage systems	Random integer search optimization	MO
[113]	Salakij et al.	Residential	HVAC	Linear quadratic tracking	MO
[114]	Mubarak et al.	Residential	Overall	Hybrid deep learning	MO
[115]	Zhou et al.	Unspecified	Electric vehicles	Adaptive neural fuzzy inference system, Gaussian process regression	MO

Artificial lighting accounts for approximately 29% of total energy consumption in office buildings [121]. Therefore, reducing lighting energy consumption is crucial for achieving ZEBs. Intelligent lighting control systems, which adjust the light based on indoor illuminance, can optimize energy use while maintaining lighting quality. Some researchers [122,123] have proposed using sensors and controllers to provide real-time lighting information and feedback.

FDD is a programmed procedure of detecting and separating flaws in BEMS. Extensive research has concluded that fault detection and diagnosis could significantly decrease energy waste and improve indoor environment quality. By data monitoring of the energy equipment, it is more convenient to determine the reasonable equipment maintenance period and types to enhance the efficiency, comfort, and reliability in ZEBs. Currently, the computing-based FDD is mainly classified into three categories, i.e., knowledge-based, data-driven, and hybrid methods. This classification method is similar to building energy modeling. More specifically, the knowledge-based approaches employ the physical principles or engineering knowledge for FDD, while the data-driven approaches directly analyze system sensing data to identify and isolate HVAC system faults. As observed, data-driven approaches are more popular when compared to the other two approaches (knowledge-based and hybrid methods), given the advancement of computing techniques [124]. Han et al. proposed a least squares–support vector machine (LS-SVM) model optimized by cross-validation to implement FDD on a 90-ton centrifugal chiller. The results showed that the proposed LS-SVM model with optimization showed a better FDD performance in terms of the overall correct rate for all the samples [112]. With more components included in the whole building, the BEMSs have become complex, which creates complex operation challenges and decreases the reliability of the system. Therefore, researchers have proposed FDD to fit into future retrofit projects, enhancing the efficiency, comfort, and reliability of buildings [125].

Management optimization (MO) in a BEMS refers to the strategies focused on “software” development. The optimization of equipment operational strategies, matching energy supply with demand, and adopting demand-side response technologies are used to achieve ZEBs [97]. The optimization of the systems involves a large variety of data processing; accordingly, the necessity of improving the efficiency and accuracy of this procedure has prompted two approaches, namely robust optimization and stochastic optimization [96]. The stochastic approach is more suitable for the questionable optimization issue, where the parameters are stochastic and obeying probability distribution, such as identifying energy consumptions patterns [126] and maximizing the general energy-efficiency performance [127]. Missaoui et al. [56] investigated the performance of a global model-based anticipative building energy management system in managing household energy consumption. The researchers used a multi-objective optimization approach that considered total energy costs and occupant dissatisfaction as the objectives and occupant expectations, energy prices, and power limits as the constraints. This approach ensures that the objective function is optimized over the long term, achieving the best possible outcome.

The robust approach focuses on the solution under the most adverse conditions in the worst-case scenario, ensuring the robustness and resilience of the system performance. There have been studies on BEMSs associated with a robust approach that focused on optimal planning of the components of the local energy system [128], supervising a multi-HVAC system [129], and managing occupant comfort and energy utilization [130]. Papadopoulos et al. [48] used the NSGA-II algorithm to adjust the set point of HVAC, achieving nearly 60% annual energy savings without compromising occupant comfort in moderate climate.

The above research has indicated that smart technologies can enhance energy efficiency through multi-energy system designs to optimize the design and operation of the energy systems in buildings to achieve ZEBs. Additionally, many scholars have focused on using smart technologies to optimize the complex procedure for processing large amounts of data streams. AI is particularly adept at identifying anomalies in data through anomaly detection algorithms but also in automating the identification and correlation of data issues, thereby reducing the need for manual intervention. For example, Shen et al. [131] defined key decision variables through digital twin (DT) and BIM, capturing data through DT integration for scientific calculations and decision making throughout the ZEB lifecycle. Zhao et al. [132] analyzed building operation and maintenance data to establish fitting equations for calibrating anomalous and missing data, providing a concise correction method for monitoring data in smart ZEBs. Ma et al. [133] proposed a method for predicting energy consumption. In this method, the simultaneous data feature similarity model was used to extract the similarity of the energy consumption data, and the XGBoost model was used to produce accurate prediction results. Research has shown that intelligent technologies used in BEMS not only enhance the efficiency of data processing but also continuously improve the accuracy and intelligence of correlations through self-learning capabilities.

6. Future Research Works

From the above-mentioned analysis, the key technological systems of ZEBs have been largely established, mainly focusing on three aspects: EEMs, RETs, and intelligent BEMS. However, several challenges remain in advancing the ZEBs research field.

6.1. Privacy and User Comfort

Numerous studies have demonstrated that variations in user behaviors significantly impact building energy consumption [134]. It is crucial to accurately capture user behaviors for enhancing the precision of energy consumption prediction models. Traditionally, building energy prediction models have relied on the static schedules of occupant behavior. However, the need to accurately capture actual user behaviors within a building has prompted scholars to explore AI-based methods, which are particularly significant for improving energy efficiency in ZEBs. Nevertheless, the effectiveness of AI depends heavily on substantial amounts of measured data. The deployment of various sensors and monitors within buildings raises concerns regarding privacy. Additionally, when addressing the multi-objective optimization issue of balancing user comfort and energy costs in ZEBs, applying such optimization techniques universally is difficult. Human thermal comfort is highly complex, and few standards can comprehensively address the diverse comfort requirements of all individuals. Therefore, addressing privacy concerns associated with data acquisition and ensuring the applicability of comfort standards across different populations are critical areas warranting further research.

6.2. Zero-Energy Communities

Community is the basic unit and functional carrier of an urban economy, society, culture, and environment. It is an important starting point to help cities achieve the goal of net-zero energy consumption. It represents a significant development goal for expanding the scope of zero-energy buildings to zero-energy communities and even zero-energy cities. The EU has introduced the concept of Positive Energy Districts (PEDs) as a model for renewable energy cities [135]. PEDs consist of energy-efficient buildings that not only generate zero emissions through the utilization of renewable energy sources but also intelligently manage energy storage systems. As a result, optimizing the DES within communities, in conjunction with electric vehicles, is worthy of in-depth investigation. Compared to achieving zero energy consumption in single buildings, extending this achievement to an entire community presents increased complexity and challenges. For single buildings to achieve zero energy consumption, the technology is relatively mature. However, in the application of renewable energy technology in the case of the building energy producer, the energy flows become more complex for full utilization of the RET-produced energy. Thus, a variety of energy-consuming equipment in the system helps to disperse the pressure of energy reserves and consumption in multiple ways. This process involves integrating buildings, energy systems, transportation systems, and other aspects of a ZEC, all of which generate a vast and complex system. Consequently, more research need to be conducted in reasonable community design, coupling the various components of the community, optimizing community energy management in order to achieve full utilization of renewable energy, and maximizing energy efficiency. The development of high-performance and broad-spectrum intelligent technologies may be favorable for realizing ZECs earlier.

7. Conclusions

The implementation of ZEB technology systems is crucial in reducing building energy consumption, mitigating the greenhouse effect, and achieving dual-carbon goals. This paper summarizes the key technologies of ZEBs, focusing on three main areas: EEMs, RETs, and BEMS. The main technologies and features of the different ZEB approaches discussed here are summarized in Table 7. The conclusions can be drawn as follows:

(1) The implementation of EEMs is crucial for promoting ZEBs. EEMs include optimized building envelope structures, and PCM aims at reducing heat loads, concerning HVAC and user behaviors as well. In areas where heating dominates annual energy consumption, improving the insulation performance of the envelope is crucial for minimizing heating demand to the greatest extent possible. On the contrary, in areas where air conditioning is prevalent, strengthening the insulation of the casing may increase cooling demand, thereby reducing its energy efficiency. The application of PCM has been strongly associated with the climate. In hot climates, PCM is superior to insulation materials and should be installed near the exterior of building envelope to prevent heat from dissipating indoors. In cold climates, insulation materials are more effective, and PCM should be installed closer to the interior of the envelope. For HVAC systems, multi-objective optimization models should be used to determine the optimal temperature set point, aiming to minimize energy consumption while maximizing indoor thermal comfort. In addition, using machine learning models to detect occupant behavior to balance energy costs and user comfort is currently the main focus of ZEBs;

(2) RETs in ZEBs mainly include solar PV, BIPV, GSHP, wind, biomass, and ocean energy, with solar PV being the most widely used. In general, most RETs need be reasonably used based on local resource conditions. RETs are key to the energy revolution, but single renewable energy sources suffer from a lack of stability. DESs with energy storage are used by the most ZEBs to ensure energy sustainability. With the complexity of the type, scope, and application scenarios of ZEBs research, the concept of zero energy has been

expanded from a single building to a community- or city-wide scale, which increases the requirements for the overall performance and predictability of the DES, and it is important to use AI technology for simulation and prediction. In the future, research on new RETs and in support of energy storage technologies should be strengthened, and new technologies such as AI for improving the stability and operational efficiency of energy systems are also worthy of further study;

Table 7. Summary of various ZEB approaches.

Energy-Efficient Measures **ZEBs approaches**	**Technologies**	**Remarks**
Improved building envelope	Improved thermal insulation Installed high-performance windows Good airtightness Heat transfer coefficient Solar heat gain coefficient Window/wall ratio Optimized orientation/building layout	When the insulation capacity of the building envelope exceeds a certain threshold, the reduction in indoor heat loss can lead to increased cooling energy consumption, ultimately raising overall energy demand.
PCM integration	PCM cold storage PCM heat storage	The effectiveness of PCMs is influenced not only by climatic conditions but also by the thickness of the material and its installation location.
HVAC systems	Ventilation (heat recovery ventilation and energy recovery ventilation) Dehumidification Heat pump (air-source heat pumps and ground-source heat pumps)	The proper thermostat set point can significantly reduce cooling and heating loads while maintaining indoor thermal comfort.
User behaviors	Home Wi-Fi usage BIM Machine learning models	Smart technologies for capturing occupant behavior characteristics can reduce uncertainties.
Renewable Energy Technologies **ZEBs approaches**	**Technologies**	**Remarks**
Solar energy	PV, PVT, BIPV, BAPV	Unit cost relatively independent of installation size.
Geothermal energy	GSHP	Geothermal energy, while more stable, requires a consistently good range of subsurface temperatures.
Wind energy	Wind turbine, wind energy systems, and wind farms	The wind energy is more unstable, but it is more environmentally friendly and particularly advantageous in specific climatic regions.
Biomass energy	GSHP	Bioenergy is unaffected by climatic conditions, and it can ensure a stable energy supply as long as there is an adequate supply of raw materials.
Ocean energy	Wind, tides, waves, and the temperature difference between deep and shallow oceans	Single renewable energy sources often suffer from a lack of power supply stability.
DES	Combined thermal storage modules with conventional DES components	DES can enhance their sustainability by enabling peak shaving and valley filling.
Building Energy Management Systems **ZEBs approaches**	**Technologies**	**Remarks**
Energy usage control	Dynamic control of HVAC and lighting	The most direct method.
Fault detection and diagnosis	Knowledge-based approach Data-driven approach Hybrid methods	Improves energy efficiency directly, but the cost is relatively higher.
Management optimization	Robust optimization Stochastic optimization	More comprehensive, but it is dependent on AI.

(3) BEMSs pay more attention to the overall management to achieve zero energy consumption. BEMS can be designed and optimized from the following three aspects: EUC, FDD, and MO. EUC focuses on the control of the equipment, for example, using a fixed schedule. However, the static and rigid control of electric devices (such as lighting, HVAC, and elevators) cannot meet the requirement of ZEBs; therefore, the optimization of EUC is vital to make it more feasible to achieve energy-saving targets. Energy-consuming equipment is an essential part of BEMS, and the energy efficiency can be improved when utilizing FDD. Nevertheless, replacing the equipment at random is not only detrimental to the cost of the investment but also leads to the possibility of entire system mismatches. MO represents the comprehensive technologies matching the energy supply and demand by

optimizing equipment operation. MO inevitably involves a large number of data streams, and therefore, more attention should be paid to AI technologies to address the control process in BEMS, which is essential to the ZEBs;

(4) More attention should be paid to user behaviors and the research on ZECs. Addressing privacy issues related to user behaviors and advancing ZECs are crucial areas for the future research. Precise and moderate investigation and recording and applying user behaviors not only improve the energy efficiency but also provide the original data of BEMSs. From the perspective of users, the research on user behaviors can take their comfort into account in order to improve productivity. ZECs represent the vision for the future development of urban cities. Achieving zero energy at the building level is a necessary step toward zero-energy communities and cities. Smart technologies can optimize multi-energy systems and address socio-economic and environmental challenges, promoting sustainable ZECs.

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Abbreviations

ZEBs	zero-energy buildings	PVT	photovoltaic thermal
EEMs	energy-efficient measures	BAPV	building attached photovoltaic
RETs	renewable energy technologies	BIPV	building integrated photovoltaic
HVAC	heating, ventilation, and air conditioning	DES	distributed energy system
U	heat transfer coefficient	ABS	absorption chillers
SHGC	solar heat gain coefficient	EVs	electric vehicles
WWR	window/wall ratio	BEMS	building energy management system
PCM	phase change materials	EUC	energy usage control
BIM	building information modeling	FDD	fault detection and diagnosis
ZECs	zero-energy communities	MO	management optimization
PV	photovoltaic	AI	artificial intelligence
GSHP	Ground-source heat pumps	IoT	Internet of Things

Appendix A Appendix A

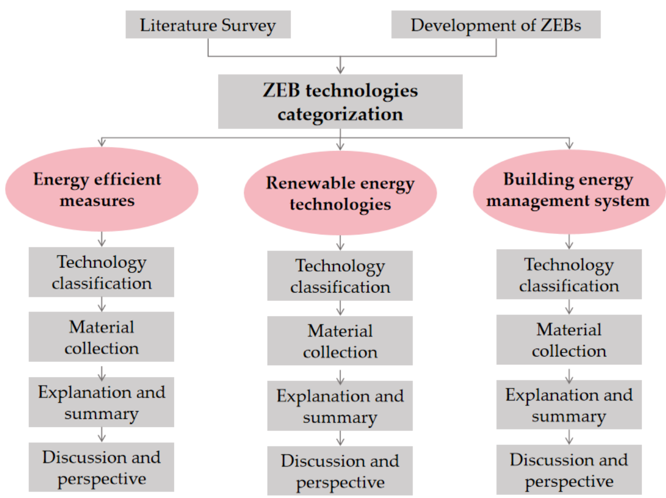

Figure A1. The framework of the research methodology in this work [136].

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