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Review

A Review on Optimal Energy Management in Commercial Buildings

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Abstract: The rising cost and demand for energy have prompted the need to devise innovative methods for energy monitoring, control, and conservation. In addition, statistics show that 20% of energy losses are due to the mismanagement of energy. Therefore, the utilization of energy management can make a substantial contribution to reducing the unnecessary usage of energy consumption. In line with that, the intelligent control and optimization of energy management systems integrated with renewable energy resources and energy storage systems are required to increase building energy efficiency while considering the reduction in the cost of energy bills, dependability of the grid, and mitigating carbon emissions. Even though a variety of optimization and control tactics are being utilized to reduce energy consumption in buildings nowadays, several issues remain unsolved. Therefore, this paper presents a critical review of energy management in commercial buildings and a comparative discussion to improve building energy efficiency using both active and passive solutions, which could lead to net-zero energy buildings. This work also explores different optimum energy management controller objectives and constraints concerning user comfort, energy policy, data privacy, and security. In addition, the review depicts prospective future trends and issues for developing an effective building energy management system, which may play an unavoidable part in fulfilling the United Nations Sustainable Development Goals.

Keywords: energy management system; intelligent energy management system; net-zero energy management system; demand side management; sustainable development goals

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1. Introduction

Global economic growth is booming with the increasing population. This will lead to higher electricity demands in the future. Statistics indicate that 44% of global energy comes from fossil fuels [1]. Moreover, building energy consumption is deemed the primary energy consumer compared with other sectors, with a high percentage of energy wastage due to poor management and the ineffective implementation of strategies. Currently, the rate of increase in global energy consumption is at 2.9%, and it is forecasted to rapidly increase in the upcoming years. Notably, the Asian regions are now consuming more electricity than the United States of America because of the trends in developing countries' economic growth. Buildings account for 40% of global energy consumption [2], and release one third of all greenhouse gas emissions while incurring energy losses ranging from 2% to 20% due to irresponsible consumer behavior and inefficient appliances [3]. Buildings in Malaysia consume 14.3% of the total energy generated [4], with 80% to 90% of the population spending most of their time inside buildings [3,4], with the majority of the energy being consumed by cooling and lighting loads. More than 94% of generated electricity resources come from the combustion of fossil fuels. As a result, carbon dioxide emissions have increased by 221%, placing Malaysia at 26th among the world's top 30 greenhouse gas emitters [3].

In the US, buildings consume approximately 40% of the entire country's energy consumption [5,6], and almost 40% of energy is used in residential and commercial buildings in Europe [7]. Buildings consumed 284 TWh of electricity in 2007, accounting for 65% of the total electricity usage in France (434 TWh). A total of 404 million tons of CO_2 were emitted, which was 22.6% of the total emissions [8]. As a result of global warming trends and rising atmospheric temperatures, the heating demand for global residential buildings will decrease by 34% in the year 2100, while cooling demands will increase by 72% [9].

Due to rising energy demands, the industrial revolution has brought with it a slew of new issues. This phenomenon fosters the development of more resource-efficient control approaches. The building sector has a huge potential to mitigate energy demand using intelligent energy management systems (IEMS) [10] and the concept of the internet of energy (IoE). The IoE combines features of a smart grid and the internet of things (IoT). The IoT refers to internet-based architecture in two ways: communication allows the system to be monitored and controlled in real time via cloud computing or another internet service [9–11]. It is proven that the potential of IoE-based building energy management system BEMS will enhance the performance of future building energy utilization [9].

The key idea of BEMS is monitoring and controlling the energy consumption in buildings with the aim of reducing emissions. The design of BEMS has taken into account factors such as efficiency, scalability, robustness, flexibility, and an ability to sense the environment and make decisions autonomously [12]. A structure of an IEMS is shown in Figure 1. The IEMS consists of an optimization controller that acts like a center controller and interfaces with the operating browser via communication protocols. In practice, the user interface allows interaction seamlessly with connected devices using the same operating browser. Weather information is also taken into account for forecasting energy consumption and generation for the day ahead. Moreover, renewable energy resources (RER), energy storage, and a standby generator for emergency purposes are also considered to reduce the dependency on the grid and compensate for the peak hour and optimal load scheduling. At present, electric vehicles (EVs) are also included, and an IEMS ensures the optimal charging and discharging of vehicle-to-grid (V2G) and G2V during peak and off-peak hours. Furthermore, by educating consumers about the concept of being prosumers, excess RER generation can be sold to the grid with both the utility provider's and the consumer's consent.

Several significant articles have been published on BEMS. Aguilar [13] and Alanne [14] discussed artificial intelligence (AI) in demand-side management to compromise energy cost and occupant comfort. However, the authors did not provide a pro and con outline of controllers and optimizations. Gong [15] focused on the consideration of human comforts and intelligent controls, whereas the authors did not discuss the objectives and constraints related to all air-indexed parameters. Parvin [16] overviewed the optimization control in building heating, ventilation and air condition HVAC systems to demand-side management (DSM) and also focused on occupants' comfort. However, the authors did not discuss reducing heating and cooling load demand to increase energy efficiency using both passive and active methods. Zhou [17] demonstrated building energy efficiency by regulating optimal loads while improving the building envelope in existing buildings. The authors, however, did not provide an outline of strategies for the energy-efficient retrofitting of both existing and new buildings, which could lead to zero energy building (ZEB). Kanakadhurga [18] presented energy management concerning the minimization of energy cost with the utilization of RER, but the authors did not overview the load's categorization as it is required for optimal scheduling. Hannan et al. [9] discussed the internet of energy for DSM and smart grids, which lead to smart cities, but the authors did not emphasize end-user data privacy and security as well as the risk management for national security. Hern [19] surveyed the literature on BEMS, considering building energy efficiency using control management strategies. However, the implementation of the energy policy for DSM was not covered in detail. The work in [20,21] discussed the rage of BEMS with respect to the UN's sustainability goals.

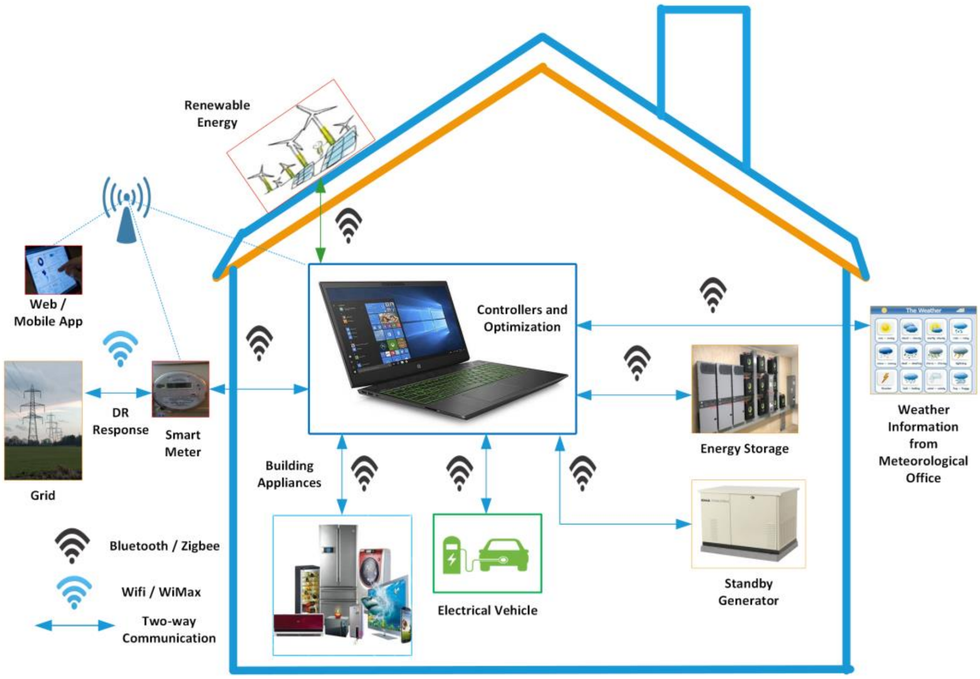

Figure 1. The structure of an intelligent energy management system in a building.

To address the gaps, this study presents a full investigation of the controllers and optimization for BEMS in terms of SDGs. The main contributions of this review are listed as follows:

- This work summarizes optimizing algorithms and various control strategies in achieving energy reduction, together with their benefits and drawbacks.
- This paper also presents the importance of commercial building load classification and categorization, energy policy, data privacy, and security to DSM.
- The subject of passive and active design solutions for energy efficient retrofitting to ZEB is highlighted.
- The study implies the development of an efficient BEMS that connects to the UN SDGs for achieving future sustainability through low carbon emissions, sustainable cities, green jobs, cost-effective energy supplies, and healthier living.

The rest of the paper is organized as follows. In Section 2, a summary of load classification in commercial buildings is described. Conventional BEMS techniques are discussed in Section 3. A thorough discussion of current and advanced methods in BEMS is included in Section 4. Furthermore, optimization control strategies in BEMS are described in Section 5. A summary of future trends and issues is presented in Section 6. Finally, a discussion and conclusions are drawn in Section 7.

2. Load Classification in Commercial Buildings

In the US, small and medium-sized building loads, specifically HVAC systems, dominate energy consumption, followed by lighting and plug loads [5]. Lighting and cooling are the most common electrical loads in commercial buildings, accounting for more than half of total electricity use, as shown in Figure 2 [22], and they are also responsible for the majority of commercial electricity costs.

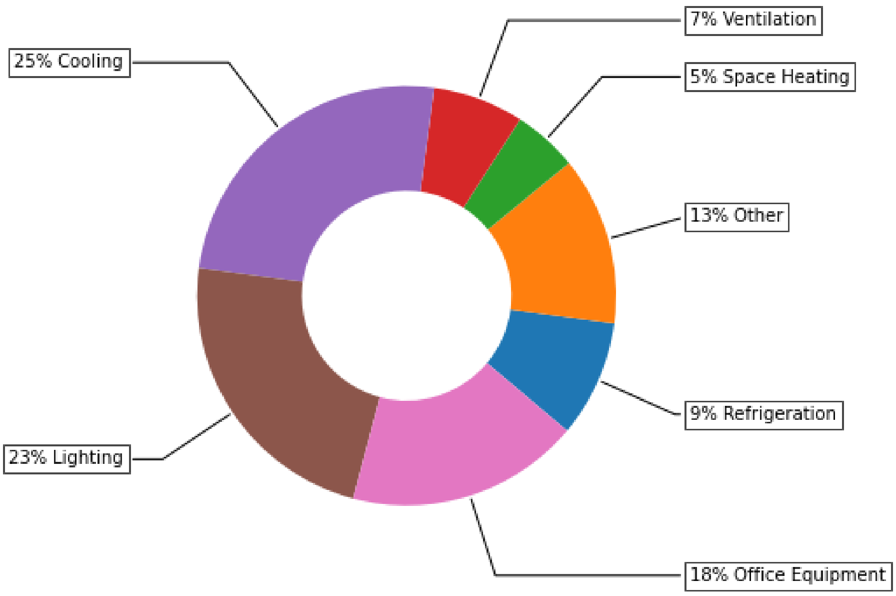

Figure 2. Energy usage data of commercial buildings in the US [22].

2.1. HVAC Loads

Heating, ventilation, and air-conditioning (HVAC) systems are utilized to regulate the temperature, moisture content, circulation, and purity of the air within a place to achieve the intended effects on the occupants of the space or the manufactured items and equipment stored there. They are used in commercial buildings all year. A typical HVAC system is shown in Figure 3. An HVAC system also refers to central air-conditioning [23]. High-capacity central systems are primarily used in large buildings. The main A/C unit is usually placed in a mechanical room, generally at a distance from the conditioned spaces. The air is then conditioned, according to the operating mode (cooling or heating) of the system. For cooling purposes, the air is cooled and, if necessary, it is also dehumidified. Similarly, for heating purposes, the air is pre-heated by passing it through a system supplied with steam, hot water, or an electric heating element. If necessary, water vapor is also added by passing it through a humidifier, and finally, the air is heated again by using steam, hot water, or an electric heating element. The central unit is connected to the air handling unit (AHU) through a duct/piping system. Then, the air is transported with fans through a duct system to individual units which are installed usually at ceiling height, floor level, or near windows, in order to ensure the best possible air circulation in each air-conditioned space. The outdoor air is introduced into the main unit and is mixed with a certain amount of recirculated air. The mixture then passes through air filters to remove any dust or other foreign particles [24,25]. In addition, a fan coil unit (FCU) is used in commercial buildings to heat or cool a room without connecting the ductwork. To condition a specific space of a room, an FCU circulates hot or cold water through a coil. The FCU draws hot or cold water from a central plant to make a human-occupied zone comfortable, with all the air-indexed properties under consideration, using a mechanical HVAC system. That results in a significant amount of energy consumption, which is associated with three factors that lead to excess electricity consumption, such as an HVAC sizing capacity that does not meet consumer needs accordingly, unnecessary usage, and lack of best practices in installation. In European countries, space cooling constitutes 40% to 60% of total building energy use. In the US, HVAC systems contribute to 50% of the energy use in buildings which is about 20% of their total energy consumption [26]. Cooling systems in the Middle East utilize more than 70% of all building energy [27]. Fan and supply air cooling account for 60% of HVAC energy use in Singapore and it is predicted to reach 70% [28]. Inefficiencies such as unneeded HVAC activity and exaggerated temperature settings waste a total of 10–40% of this electrical energy [29]. Without a doubt, due to economic growth and rising occupant comfort demands, the global energy demand for buildings will continue to climb in the foreseeable future.

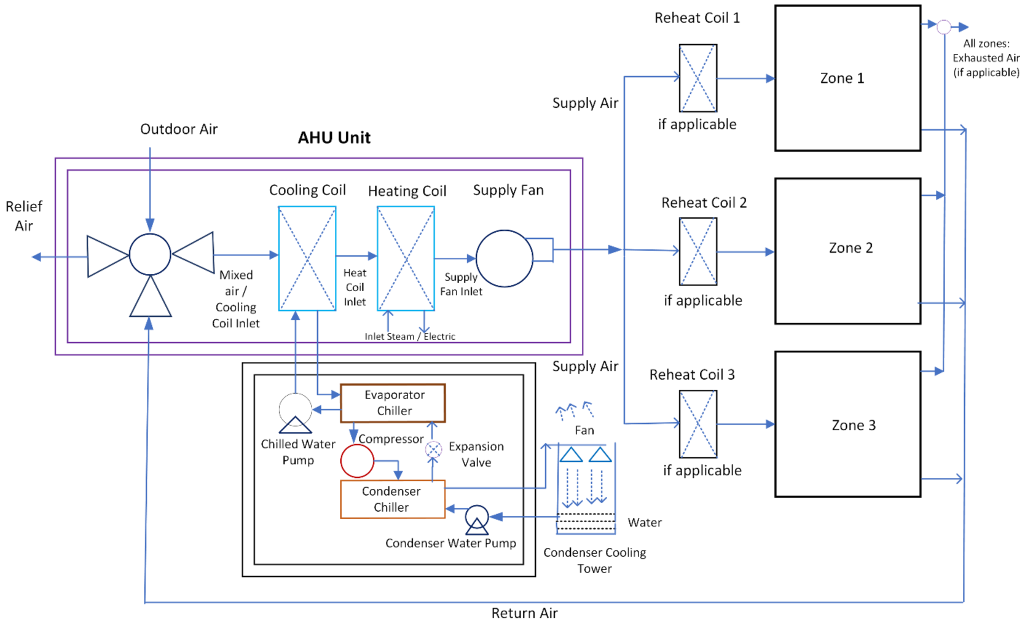

Figure 3. A typical view of a HVAC system.

2.2. Lighting Loads

When it comes to energy use, commercial buildings are crucial and utilize over one-third of the total primary energy needs of the US [30]. Undoubtedly, artificial lighting is one of the most common sources of power in commercial buildings, accounting for around 17% of overall energy usage [31]. In [32], office buildings were analyzed separately and lighting energy demand accounted for 25–35% of total energy usage. As a result, reducing the lighting load in commercial buildings can have a significant impact on lowering power demands, which in turn helps to reduce the carbon footprint [33], and is currently a major emphasis for energy engineers. Various countries, international, and regional organizations advocate specific energy-saving criteria for lighting systems [34]. Manual lighting controls are mostly based on human behavior, occupancy patterns, and general energy conservation awareness [35]. Different types of switching systems can be used to control lighting at the user level. In addition, a large number of investigations show how to improve lighting efficiency from control schemes, which involve maintaining optimal lighting conditions while using as little energy as possible [36].

2.3. Plug Loads

Water heaters, refrigerators, freezers, and clothes dryers are important energy consumers, accounting for roughly 18% of total building energy consumption. Around 36% of building energy demand is spread across a variety of systems, the bulk of which are electric. For example, computers, televisions, imaging equipment (e.g., printers and multifunction devices), audio/video equipment, telephone devices, kitchen, and household appliances, as well as kitchen ventilation are all included in commercial building plug loads [37].

2.4. Plumbing and Sanitation

Multi-story buildings are constructions having more than one story, but in the context of plumbing, a multi-story building is one that can't be fed entirely and effectively by the municipal water supply due to inadequate pressure [38]. A normal two-story building can be supplied by water main pressures of 8–12 m (25–40 feet), while higher buildings may require pressure booster systems. Multi-story structures also necessitate drainage, sewage, and ventilation systems that can accommodate a large number of people living in a vertical layout. Drains from plumbing fixtures are connected to vertical drain stacks in a multi-story building's drainage system, which transport waste and sewage to below the building's lowest floor. All plumbing fittings below ground level should be pumped into the sewer or a drainage system that leads to the sewer [39]. Tianjin Tiejian Tower consumes energy in terms of plumbing and sanitation which is 0.6% of all its energy consumption [40].

2.5. Fire Protection

Electrical fires in commercial and industrial facilities can result in significant losses in terms of business continuity, opportunity costs, assets, and output loss. Electrical fire risks from overcurrent, overvoltage, and the overheating of electrical appliances can be decreased if an electrical design adheres to requirements, including International Electrotechnical Commissions (IEC) standards and national regulations, and uses compliant equipment. Electrical installations, on the other hand, can deteriorate with time owing to environmental conditions such as heat and humidity. It is critical to comprehend the operation of fire alarm systems. Different systems work in different ways, but they all have the same goal: to detect a fire and protect the structure, its residents, and valuables [41]. As reported in [40], the energy consumption of Tianjin Tiejian Tower for fire protection equipment is 2.8%, which ensures that consumption growth will increase in the upcoming years.

2.6. Data Networks

Network access has become practically ubiquitous, and the energy consumption of the equipment necessary to provide it is increasing. Edge devices such as PCs, servers, and other sources and sinks of Internet Protocol (IP) traffic are notably excluded from this category, which comprises devices that primarily switch and route IP packets from a source to a destination. A case study was conducted on networks on a campus, in a medium-sized commercial building, and in a typical residence. It was estimated that network equipment in the US consumed 18 TWh in 2008, or about 1% of total building power, and that consumption would rise at a rate of roughly 6% per year to 23 TWh in 2012; global usage in 2008 was 51 TWh. Furthermore, network switches in office buildings and residential equipment are the two most energy-intensive groupings, accounting for 40% and 30% of total energy consumption, respectively [42].

2.7. Transportation

The transportation and building sectors are two important areas for electrification. Light-duty electric vehicle (EVs) adoption for consumer ownership dominates transportation electrification. Light-duty EVs for personal use are driving transportation electrification and are frequently classified into plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). In 2018, about 1 million EVs (around 0.5% of all vehicles) were registered in the US. By 2021, another 1 million EVs were estimated to be registered [43]. EV sales currently account for 1–2% of the light-duty market, and they are predicted to grow consecutively [44]. EV sales projections vary widely, but realistic estimates include 7–12% adoption by 2030 and 11–48% adoption by 2050 [45]. The 0.58 million EVs sold in the US utilized around 1 TWh of electricity in 2017. By 2025, electricity consumption is expected to reach 33 TWh per year, rising to 551 TWh by 2040 [43]. In the near future, transportation, in particular, is predicted to have the greatest impact on power usage. Uncontrolled EV charging is a huge barrier to grid operations, but control solutions offer a way to boost efficiency [46].

2.8. Miscellaneous

Lifts and escalators are also included in commercial buildings, which consume 3.3% of the entire building consumption [47]. There is potential to conserve energy by using automation based on occupancy presence along with a variable voltage variable frequency drive (VVVFD) as an induction motor. A power factor improvement will be required to minimize the operating costs. In addition, people are encouraged to use the stairs if the lift and escalator are less conveniently located, which may help meet the LBC's "Health" petal [48]. In addition, street lighting, garden lighting, safety, and security (e.g., CCTV and RFID) equipment are also responsible for consuming electricity in commercial buildings.

3. Conventional BEMS Techniques

Building control systems are critical components in achieving energy efficiency and long-term sustainability in buildings. A few traditional control systems for load monitoring, such as (i) thermostats, (ii) proportional–integral (PI), and (iii) proportional–integral–derivative (PID), have been extensively used in conventional BEMS. These control systems have also been used in a variety of applications and disrupted environmental situations, and they have consistently performed poorly and do not provide an optimal control approach [49].

3.1. Thermostat

ON/OFF is one of the most basic and often-used control modes. This mode can be used in building HVAC, lighting, and shading systems [50]. A thermostat is a device that regulates the temperature within a user-defined range [51]. When the temperature falls below the set point, the thermostat turns off the power, and then restores it when the temperature rises above the set point [52]. A typical structure of a thermostat is shown in Figure 4. Thermostats can be found in water heaters, ovens, refrigerators, and HVAC systems and are often used for heating or cooling to a fixed-point temperature. In BEMS, the thermostat is used to minimize power fluctuations [53], lower cooling electricity costs [54], control space heating [55], improve thermal comfort [56], and increase energy efficiency [57]. Although this approach offers the simplest ON/OFF control operations which occur frequently in the system, when the controlled device is turned on, it constantly operates at maximum or default capacity, consuming a large amount of power in each action [58]. Furthermore, the ON/OFF action may cause oscillations in the controlled temperature, resulting in energy waste. In some complicated energy systems, ON/OFF-based controllers are ineffective to achieve control variables and objectives with merely discrete ON or OFF values [59].

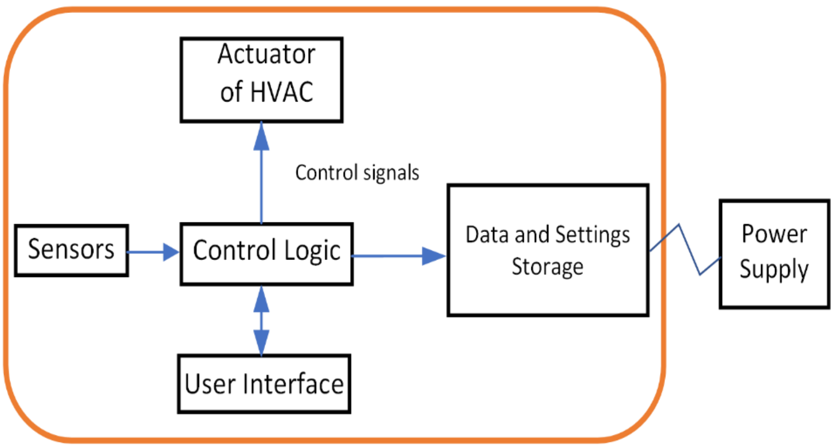

Figure 4. A typical structure of a thermostat.

3.2. PID Control

All three types (proportional, integral, and derivative) of action are utilized in most digital controllers to incorporate advantages such as removing offset and speeding up the response of the control function. In a nutshell, the integral control function tends to destabilize the system, whereas the derivative control function tends to reinforce it. The integral function is frequently used to reduce or eliminate the offset of proportional control and to provide more precise control. A typical structure of a PID controller is shown in Figure 5 [60]. The time domain function of PID control is shown in Equation (1).

$$u(t) = K_P\left[e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau + T_d\frac{de(t)}{d\tau}\right] \quad (1)$$

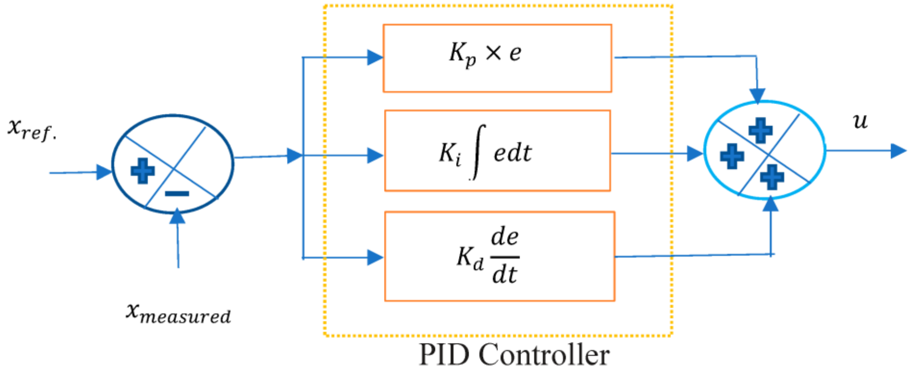

Figure 5. A structure of PID controller [49].

The transfer function of PID control can be written in "Ideal form" and "parallel form", respectively, as shown in following Equations (2) and (3).

$$PID(s) = K_P\left(1 + \frac{1}{T_i s} + T_d s\right) \quad (2)$$

$$u(t) = K_P e(t) + \frac{1}{K_i}\int_0^t e(\tau)d\tau + K_d\frac{de(\tau)}{d\tau} \quad (3)$$

where, K_P, K_i, and K_d denote proportional gain, integral gain, and derivative gain, respectively. T_i and T_d are integral and derivative time constants, respectively. Since P, PI, and PID controllers are closed loop/feedback controls that have constant parameters and do not have a direct knowledge of the system to be regulated. When utilized alone, they give poor control performance for noisy and non-linear processes with long-time delays [61]. In general, the PID controller has been effectively used in a variety of building sections, including lighting management [62], tracking performance improvement [63], and energy consumption reduction. There is no doubt that PID performance is more efficient than thermostat [64]; however, there is still a demanding task of choosing the suitable settings of K_P, T_i, and T_d, respectively. In addition, when integral functions are introduced to eliminate the offset of proportional control to obtain a more accurate control of variables and objectives, their effect might cause the system to oscillate and deteriorate control [49]. To tackle these issues of PID controllers, optimization control strategies in BEMS are explained in Section 5.

3.3. Energy Efficiency

In the context of global initiatives for sustainable development, a commitment to energy-efficiency improvement is becoming increasingly crucial, and buildings have a lot of potential in this area. Energy efficiency allows you to use less energy while maintaining the same level of service. To permanently minimize demand during peak and off-peak periods, energy efficiency measures are implemented as part of normal operations. Energy efficiency in buildings is often achieved through efficient building designs, energy-efficient equipment, and efficient building operations. Since efficiency measures are a long-term feature of normal operations, they are usually distinguished from demand response (DR), which involves only short-term changes to normal operations [65]. The following two types of energy efficiency measures, such as passive and active strategies, are used in buildings.

3.3.1. Passive Methods

The use of energy in many buildings can be greatly decreased by implementing passive techniques. These methods may not necessitate additional financial resources. For example, an integrated building rehabilitation approach that incorporates passive approaches can reduce a building's energy usage while also compensating for the higher cost of new technologies [66]. Passive energy conservation strategies aim to reduce energy demand by maximizing the use of natural heating, cooling, and lighting resources, as well as limiting energy losses through the building envelope [67].

Traditional buildings used to be built with climatic conditions in mind and incorporated passive cooling and heating methods for both summer and winter, respectively. Most buildings nowadays have mechanical or active heating, cooling, and lighting systems, which consume a lot of energy [66]. Passive methods, such as the use of solar energy or creative architectural design, can greatly reduce total energy usage in a building. Passive solar energy is becoming increasingly popular. In 1974, a large south-facing window was used as the first passive solar heating system in New Mexico [68]. Using direct or indirect passive solar energy to alleviate heating, increase cooling capacities, and reduce a building's energy consumption is a basic approach, taking advantage of free solar energy [69]. In the winter, solar energy is used to warm the indoor atmosphere to a comfortable temperature. Solar radiation is absorbed directly through the transparent parts of the building exterior, particularly those facing south. This radiation is converted to heat, which elevates the temperature within the house. Solar radiation can also be employed as a source of natural illumination. Indirectly, solar radiation can be utilized in the winter. Multi- or double-skin façades, Trombe walls, and linked sunspaces are all popular methods for indirect solar advantages [67]. The effect of different insulating materials, construction systems based on sustainable materials, the incorporation of thermal energy storage (TES), phase-change materials (PCM) in building envelopes, and green infrastructures such as green roofs and walls are among the research fields of passive technologies [70]. By lowering the energy demand in buildings, passive energy techniques could reduce reliance on fossil fuels and capital-intensive renewable energy technologies. However, understanding building science ideas and energy control principles is essential for the effective implementation of these strategies.

3.3.2. Active Methods

Active energy-saving technology has also been widely employed to lower the energy consumption of buildings. Active measures include enhancing HVAC systems, energy-efficient appliances, lighting systems, and the use of renewable energy, as well as distributing energy as efficiently as possible while ensuring occupant comfort [67]. The active systems were also designed to take advantage of various renewable energy sources, such as solar thermal, free cooling with night air, or geothermal heat, by utilizing thermal energy storage systems to shift heating and cooling loads [71].

To improve a building's energy efficiency, a variety of active approaches have been adopted. Heat pumps and boilers, for example, are active tactics in traditional air-conditioning. Furthermore, advancements in compressor technology and hybrid systems help to increase heat pump efficiency [72]. Active techniques, on the other hand, have some insurmountable restrictions. A heat pump's coefficient of performance (COP) is rarely greater than six, whereas a boiler's combustion efficiency is far less than 100%. Heat pumps and boilers are used in HVAC systems to overcome a significant temperature difference between indoor and outside temperatures (e.g., 10C in summer and 20C in winter). Inevitably, this would result in the system's overall energy efficiency being low [73].

Substantial energy savings can also be achieved in existing mechanical HVAC systems. Air conditioners that are properly maintained can reduce peak demand, conserve energy, and save running expenses. Correcting low air-flow rates, rectifying refrigerant overcharging and undercharging, and addressing duct leaks are just a few examples of individual repair techniques. Heat pumps and other high-efficiency mechanical systems can be used to replace older technology equipment in applications where air-conditioning is required, resulting in significant energy savings [24].

After HVAC systems, lighting uses a significant amount of electrical energy in buildings. Lighting efficiency is the most cost-effective active technique, and air conditioning efficiency was the second [74]. A well-designed lighting system can conserve energy while also providing the maximum visual comfort to building occupants [75]. Standard groups such as the European Committee for Standardization have developed standards to guide and provide specifications and requirements for technological systems in order to achieve lighting system energy efficiency in buildings. The European Standard EN12464-1 (i.e., for interior design) [76], the European Standard EN12464-2 (i.e., for external design) [77], and the European Standard EN15193 (i.e., for lighting system) [78], and the European Standard EN15193 (i.e., for performance evaluation) [79]. LED is a prominent energy-efficient lamp, used in lieu of conventional lamps, with a greater photometric performance (e.g., luminous flux, color rendering index, and luminous efficiency) and easier to regulate when compared to other lamps [75]. The regulation of a lighting system is the most important factor to increase energy savings in buildings, and it has received a lot of attention from researchers in the previous decade. Lastly, it is recommended that traditional appliances should be replaced with five-star energy-efficient appliances [80]. Many other energy-saving strategies are also employed in a low-energy-consumption structure. Included are energy-saving air conditioning designs, equipment energy-saving, behavior energy-saving, and energy-saving by operation adjustment, among other things.

In summary, active and passive techniques each have their own set of benefits and drawbacks, and neither can be considered a replacement for the other [81]. To take advantage of the benefits of both tactics, a growing number of passive strategies are being coupled with active strategies or used actively. As a result, a combination of passive and active technology is both promising for energy savings and good interior environment assurance.

4. Current and Advanced Methods in BEMS

Intelligent automated control systems are introduced in current and advanced methods of BEMS, and are capable of minimizing energy usage while respecting the comfort and actions of building occupants [82]. The control of energy-related smart devices and appliances in a building is referred to as smart energy building control. It is based on a predetermined strategy and policy, as well as user choice if desired. These control systems are centralized, integrated hardware and software networks that monitor and regulate the indoor climatic conditions in buildings. These control systems are typically used to safeguard buildings' operational performances as well as the safety and comfort of their residents [83]. Finding the optimal trade-off between occupant comfort and total energy usage is a fundamental challenge for building control. Several building control systems and methods for building energy and comfort management have been presented [84], both in the research and commercial fields, with the goal of attaining energy savings through intelligent control.

4.1. Automation

Energy management is a fundamental function of building automation systems. Building automation concepts and applications are not new, having been introduced by Warren S. Johnson in 1985 [85]. The term "Building Automation System" (BAS) also known as "Building Management System" (BMS) refers to a collection of systems that control the operation of a structure. Notably, a BAS is one of the most important intelligent building systems [49]. The system is also referred to as an Energy Management and Control System (EMCS) or a BEMS, rather than a BAS or BMS, if the main reason for installing it is to save energy [86]. As a result, an EMCS or BEMS is typically included in a BAS or BMS. EMCS or BEMS can be implemented as the monitoring and control systems for building service (HVAC systems, electrical systems, lighting systems, fire systems, security systems, and lift systems are all examples of building services) systems that have a substantial impact on building energy usage [49]. Figure 6 illustrates the hierarchy of building automation systems. Meanwhile Figure 7 shows the steps of BAS development steps [78–88].

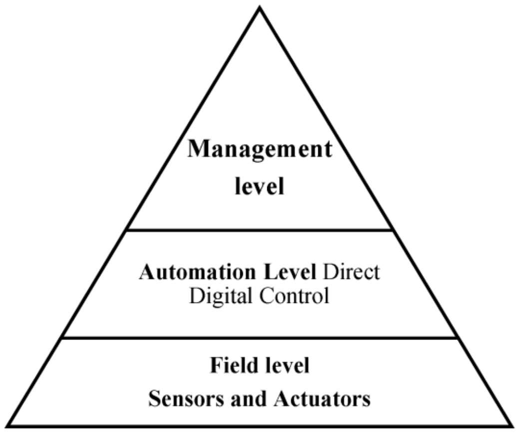

Figure 6. Hierarchy of building automation systems.

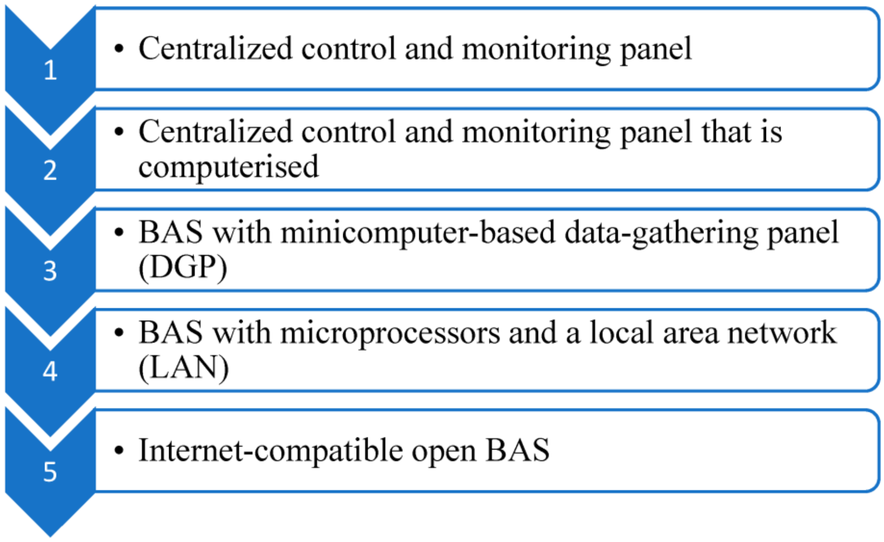

Figure 7. The steps of the BAS development process.

BAS systems are mostly processor-based [89]. A communication network is built into the BAS and extends across the building or set of buildings. In the event of smoke, fire, intrusion, or other events that could potentially harm equipment, this same communication system can be used to send alarms to an operator or security agency. In addition, this is accomplished through strategies such as load duty-cycling to save energy, peak load management to control total power consumption during peak hours, the scheduled start/stop of building HVAC systems at the start and end of each day, and the real-time control of building systems in response to occupancy detection, all of which are possible with BAS. Moreover, a BAS has made it possible for buildings to respond dynamically to current weather conditions, room occupancy, time of day, and other inputs, resulting in significant energy savings. To increase energy economy and occupant comfort, a BAS allows the centralized administration of climate control, lighting, and security systems [90]. These solutions help to cut down on energy waste and expenditures while also increasing occupant productivity.

4.2. Intelligent Devices

Intelligent devices are referred to by a variety of names, including intelligent instruments, intelligent sensors, smart sensors, and smart transmitters. However, because there are no universal definitions for these terms, devices with similar characteristics but from different manufacturers may be called by different names [91]. The objective of intelligent buildings is to integrate intelligence directly into manufactured building equipment and components, allowing them to transmit information via standard protocols for intelligent system operations (control, maintenance, and service) [92]. Most building components, including individual lights, sensors, compressors, valves, heat exchangers, pumps, freezers, and dishwashers, could eventually be connected with embedded intelligence. Remote diagnostics and pricing estimates for appliance repairs could be provided by service providers. Reduced downtime, service costs, and utility expenses are the most important advantages of automated fault detection and diagnostic systems for heating, ventilation, and air conditioning and refrigeration (HVAC&R) equipment. Even though major commercial buildings use computer control and monitoring systems, they do not currently have many diagnostic capabilities [93]. In addition, appliances could be built to be grid friendly, responding to utility management or pricing signals and coordinating themselves to reduce electrical usage during peak demand hours.

Consumers are increasingly profiting from technological advancements, and intelligent devices such as the smart controlling of light, HVAC systems, smart plugs/sockets, and other intelligent devices which provide more convenient and efficient services. To improve maintenance efficiency, most intelligent devices are now connected to the central server of their relevant carriers via network optical fibers [94]. In order to achieve intelligent D2D (device-to-device) communication, devices will require intelligent routing protocols [95].

4.2.1. Advanced Metering Infrastructure (AMI)

Smart meters, communications networks, and data management systems are all part of the AMI, which allows utilities and customers to communicate in real time. The system can automatically and remotely assess electricity usage, connect and deactivate service, detect tampering and theft, identify faults and outages, and monitor voltage, among other features that were previously unavailable or required manual intervention [96,97].

4.2.2. Smart Thermostat

HVAC&R smart controlling management has become a major concern for both residential and commercial buildings. A smart thermostat is a device that learns user temperature preferences and is utilized in thermostatically regulated loads. It also makes things easier for customers by allowing remote access and communication with AMI based on price indications [98]. The smart features of programmable thermostats include sensing, machine learning, and a network connection. These thermostats are equipped with proximity and motion sensors, and their learning algorithm adapts to the user's past preferences at various times of the day. Various strategies have been investigated to sense the real-time occupancy/vacancy of HVAC zones in order to save energy without affecting occupant comforts, such as Radio Frequency Identification (RFID) [99], IR motion sensors [100], and programable thermostats [101]. However, the accuracy of detecting the occupant in a conditioned space is being questioned using a smart controller. To avoid this issue, the study in [29] describes a new wireless device platform and prototype development that combines an infrared (IR) and an optical (OP) camera to enable collaborative intelligence with minimal power consumption and improved accuracy. The system saves up to 26% of HVAC energy when compared to a programmed thermostat and schedule-based HVAC control.

Furthermore, the availability of embedded intelligence in HVAC&R equipment might significantly reduce the cost of applying intelligent control systems, allowing for a much broader applicability. A cooling tower fan controller, for example, may have access to embedded performance data from each tower fan and chiller on the local network. Likewise, a chiller sequencing controller may obtain part-load information from individual chillers [88]. In addition, a compressor might have an embedded chip with a performance map and sensor inputs for suction and discharge conditions, allowing the map to be used to calculate refrigerant mass flow rate and compressor power consumption. Similarly, a condenser might contain a chip with a model, state variable readings, and a virtual refrigerant mass flow measurement to offer a virtual sensor for condenser airflow. The airflow through the condenser might therefore be used as a diagnostic signal for fouling or fan issues [93]. In addition, the spread of low-cost information for monitoring, diagnostics, and greater control can be enabled through embedded intelligence.

4.2.3. Smart Lighting

For intelligent lighting control, the study in [102] presents a low-cost, wireless, simple-to-install, adaptive, and smart LED lighting system that adjusts the light intensity automatically to save energy while retaining consumer pleasure. The system uses Zigbee connectivity to combine motion and light sensors in a low-power wireless solution. To conduct a daylight adaptive closed-loop control, researchers suggested a smart lighting control approach that incorporated linear optimization and neural networks (NN). The proposed method used a NN to learn the impact of each luminary on the zone's maintained illuminance and modify the luminary dimming levels to achieve the desired illuminance [103]. Implementing intelligent lighting control systems, such as the integration of sensor technologies (occupancy and light sensors), advanced architectures (wireless and network-based architectures), and intelligent control techniques (artificial intelligence and optimization), has a significant potential to reduce energy consumption. Furthermore, an intelligent control system can improve occupants' visual comfort while lowering electricity use [104].

4.2.4. Smart Plugs

A smart plug is an electric device that transforms regular household equipment into smart devices. In addition, a smart plug is able to determine the type of connected home appliance based on the appliance's energy consumption profile. It can connect to a wireless home network using inbuilt wireless communication protocols so that a user can measure energy usage and control the electronic device which is plugged into the smart plug over the internet [105]. A remotely controlled intelligent power outlet system that is specifically designed to detect electrical events in low-current loads. The power outlet of the proposed system comprises a microcontroller, a ZigBee interface, an RFID reader, a relay, and a current sensor. The system's main functions include the remote management of the power outlet, real-time monitoring of current consumption, customization and programming of the power supply time schedule, automated vampire current cut-off, and protection of certain types of electrical fires and electrocutions [106]. Smart plugs can be used to manage legacy devices such as water heaters, pool pumps, and lighting fixtures that do not have inbuilt controllers or communication capabilities. Smart plugs are smart power outlets that have measuring and communication capabilities, allowing for device energy monitoring and remote device shutdown.

4.2.5. Smart Appliances

Inbuilt controllers or communication abilities in smart appliances use IoT technology to communicate with smart devices such as smartphones and tablets, giving the homeowner remote access [107]. These appliances can also communicate with the smart meter wirelessly and help to reduce energy use by automatically adjusting to changes in power availability and dynamic tariffs. The advantages of smart appliances include the ability to run in energy-saving modes or defer operation until prices fall below a certain threshold when electricity prices are high. Smart dishwashers, for example, may receive DR signals and postpone wash cycles until off-peak periods; microwave ovens might automatically cut power levels during peak periods; and refrigerators might delay defrosting operations until off-peak periods [108].

4.3. Uses of IoT in BEMS

Any device that can be controlled and monitored over the internet is referred to as an IoT-based load, and it can be implemented in BEMS to monitor and control loads, thereby saving energy that is purposefully wasted by human behaviors [109]. Achieving smarter buildings by deploying IoT devices is called home automation. In [6], the open-source software known as building energy management open-source software (BEMOSS) was introduced, which can run on a single board computer such as Odroid to control and monitor IoT devices in buildings. BEMOSS allows the user to access the supported IoT devices remotely via the web or an app to seamlessly control and monitor them in real-time [5,6]. Building and implementing a smart home using Long Range (LoRa) can be one of the most effective solutions in the IoT. The system works for both short-range and long-range, utilizing multiple communication technologies: LoRaWAN, a server-based LoRa gateway, and Bluetooth connectivity. The adopted system can communicate without a Wi-Fi connection or internet network as it uses LoRa RYRL400 to control the appliances in the home, which is dependent on radio frequency [110].

Reducing energy losses and unnecessary electrical consumption allows the identification and tracking of multiple users by internal Wi-Fi handover using a smartphone. Furthermore, innovative outlets (IO) and the IoT concerning NFC (near-field communication) identification can be used to extract accurate data about consumption, electric current, and voltage along with the identification of electric household appliances. Thus, the objective of this architecture is to identify the user location and persons in the room, and what appliances they are using and consuming with an interoperable middleware solution that provides the option to help the consumer optimize their consumption [111]. The emerging usages of the IoT in real life ease the quality of life and lead to cities being more sustainably developed without impacts on the environment, by addressing the production of devices and interfaces with hardware, energy efficiency, cyber security, e-waste, and cost-effectiveness. Not only is the usage of IoT devices required but also a focus on device recycling, as harmful materials are involved, alongside having a low consumption rate with a better life span. Moreover, to monitor and control the smart grid (SG) and DSM, the data needs to be processed in real time as the purpose of implementation is to reduce the desired electricity consumption [112].

4.4. Demand Response (DR)

DR is a set of actions that reduce or shift electricity to improve electric grid dependability, manage electricity costs, and provide systems that incentivize load shifting or shedding when the grid is near capacity or electricity prices are high. The development of DR has been highlighted as a critical national goal for improving electricity markets and system dependability [113]. The purpose of DR solutions is to reach the electric shed savings targets while minimizing any negative consequences for building occupants or processes [114]. Direct load control (DLC) and indirect load control (ILC) are the two main categories of DR approaches (ILC). DLC is a program in which utility companies reward customers for having direct control over their chosen loads. The ILC technique, on the other hand, allows AMI to participate in the optimization process. With distributed decision makers, the utility grid shares either the day-ahead load profile projection, the dynamic energy retail price, or both. All consumers have access to this information, and by using it, they might strive to enhance their benefit (i.e., lower their consumption cost) cooperatively or competitively [115,116].

Home appliances can be classified into three categories based on their potential to participate in DR: baseline loads (lighting, cooking stove, etc.), burst loads (clothes dryer, dishwasher, etc.), and regular loads (HVAC system, refrigerator, etc.), with implemented numeric and logistic algorithms that are solved based on the finite state machine (FSM) and spring algorithm [117]. To obtain the desired goal, a unique technique of arrangement of those household loads is divided into NINSLs (non-interruptible and non-schedulable loads), INSLs (interruptible non-schedulable loads), and SLs (schedulable loads), and solved with a genetic algorithm [118]. The proposed model has shown three categories of loads: fixed, flexible, and uninterruptible, which are optimally scheduled under the time of use (TOU) tariffs based on mixed-integer linear programming (MILP) to minimize consumption and cost [119].

Moreover, DR is currently a viable approach for dealing with the problem of growing peak demand on the grid. In order to reduce peak energy consumption or demand, the scheduling of residential or industrial energy use in each appliance is optimized [120]. In [121], an interactive control unit approach was demonstrated that uses peak clipping techniques to reduce peak demand with a day-ahead scheduling mechanism that uses load shifting strategies to optimize the load. A new heuristic demand response technique has been developed for appliance consumption scheduling in order to decline the peak-to-average ratio (PAR) of power demand [116]. Peak demand can also be reduced through load shifting from on-peak to off-peak or enhancing TOU tariffs [122–124]. If the consumer is not interested in rescheduling the loads for off-peak hours, they may increase the temperature of the HVAC system. As a result, consumers could feel somewhat uncomfortable for a while, but be able to decrease the temperature setting during off-peak hours [125]. In the same way, lighting intensity can be reduced and increased during on-peak and off-peak hours, respectively. A smart plug can be utilized to prevent phantom power. If the priority of comfort is determined by consumer needs over time, the time gap must be filled with either renewable energy (RE) or energy storage systems (ESS). The presence of PV and EES can help to maintain the indoor temperature by using inverter-based AC, with ESS compensating for peak-hour demand and when there is less RE generation [119]. Coordinating the operation of electric vehicles (EVs), PV units, and BESS with an improved decision-tree-based algorithm can be used reduce peak demand in residential distribution networks [126]. The peak reduction in power and prediction of long-term load forecasting for over 300 homes were studied, focusing on peak shaving and load shifting with intelligent devices [15]. The idea was to minimize the total energy usage and peak demand by regulating HVAC systems, water heaters, and batteries so that both utility authorities and consumers could benefit. There are significant opportunities to reduce energy consumption by optimizing the loads on different chillers or heat pumps, such that their (variable with the load) COP is maximized. Futuristic, intelligent homes might integrate information technology and provide the opportunity to incorporate other innovative technologies such as PV, intelligent devices, and energy storage.

5. Optimization Control Strategies in Bems

The majority of commercial BEMS on the market today are reactive rule-based. This indicates that when an event occurs, an action is triggered. As a result, these systems are unable to forecast future situations or anticipate events in order to optimize building operations [127]. To overcome these issues, users can manage their energy use at home more efficiently by optimizing their use of resources and assets. The process of identifying the circumstances that provide the highest benefit or the lowest cost of a process is known as optimization. The fundamental goal of optimization in published studies is to reduce the PAR in load demand and customer electricity costs while maintaining comfort [105]. The various optimization control strategies utilized in prior works are reviewed in this section.

5.1. Uses of Intelligent Controls in BEMS

Several research works have been carried out on different intelligent methods for BEMS, and the most used are categorized as: (i) learning based methods of the AI domain, including a support vector machine (SVM) [128,129], K-nearest neighbor (K-NN) [128], artificial neural network (ANN) [130], reinforce learning (RL) [131], etc.; and (ii) model-based methods, such as the model predictive control (MPC) technique [132].

A learning-based control model where self-scheduling loads and the ESS of the building ensure the maximum usage of PV power, curtailment load profiles, and a reduced energy cost. The optimization algorithm optimizes the building cost and minimizes the fluctuation between PV generation and energy consumption, relying on predicted control information using a machine-learning algorithm [11]. In addition, it demonstrates the benefit of combining model-based and learning-based control methods into a single management framework for controlling multiple aspects of building performance [11,133].

The predictive algorithm model of energy consumption in smart buildings with a Microsoft Azure cloud-based machine learning platform wherein three methodologies namely SVM, K-NN, and ANN have been adopted for comparison to find the most accurate prediction model as compared to actual demand. Notably, the collected data is partitioned between 70% training data and 30% testing data. Though it took the most time to train, SVM was able to predict more accurately than the other two. The K-NN approach, on the other hand, was faster at completing the training, and ANN was faster than SVM, but it took many hours. However, a high training time is required for the SVM model to achieve a higher performance [134]. Most researchers focus on maintaining the indoor comfort of the buildings by implementing complexity prediction algorithms with higher cost and computational time, and power consumption. The model is carried out and investigated on five standard supervised machine learning models: polynomial regression (PR), support vector regression (SVR), random forest (PF), extreme gradient boost (XGB), and neural network (NN). In contrast, the best result output is shown for the SVR model with a tiny prediction error. A trustworthy NN model needs extensive data training set input and more processing time, while the amount of data is relatively small in the proposed system application, so it is rational to avoid the NN [135].

A novel deep neural-network-based algorithm for the day-ahead hourly energy consumption profile prediction of residential and commercial buildings in terms of occupancy rate and seasonality was investigated. A survey was conducted by a business manager, an electrical engineer, and a data scientist about all machine learning techniques, in which deep ANN achieved the highest score (multi-criteria analysis = 189) with a high accuracy prediction rate of about 98%. Firstly, training data was generated using synthetic load generation, where 100,000 data set points (load profiles) were produced for each occupancy rate type. The proposed forecasting model introduced these data to train an eight-layer deep neural network-based model and made decisions based on a limited number of inputs, evaluated using root mean square error (RMSE) and the coefficient of determination metrics [136].

Q-learning-based peak load reduction (QL-PLR) uses RL to present the optimal residential energy management (REM), which can decline only peak load demand and is associated with the dissatisfaction of consumers [137]. The designation of a dueling deep Q network (DDQN) captures the real-time state of the grid, demand-side strategy for interruptible loads (IL), along with the safe limit of regulating the system voltage and a reduction in peak demand loads, and the operation cost of distribution system operators (DSO). It is noteworthy that deep reinforcement learning (DRL) is adopted with DDQNs to optimize the DR management of IL under the TOU tariff and variable patterns of electricity consumption. To obtain the long-term profit for the DR management problem of IL, the Markov decision process (MDP) was formulated and solved using a DDQN-based DRL algorithm [133]. In addition, in comparison to a rule-based control (RBC) policy, DRL may also be utilized to control thermal storage in commercial buildings and can lower system operating costs by more than 50% [133].

MPC has a high level of efficiency in a building's energy management. On the other hand, finding a good control-oriented model for MPC is a difficult task. To address this issue, data-driven models are applied to MPC tasks that have universal approximation capabilities [138]. To improve a building's performance and take advantage of the TES's operating flexibility, an MPC technique was devised. The findings revealed that having a TES in a commercial building allows for more flexibility in participating in DR programs, resulting in lower energy costs and demand charges while maintaining occupants' comfort [139]. In the presence of an ESS, MPC was utilized to control the functioning of a commercial building in DR programs for bi-directional power flow with the main grid. The results of this study demonstrated that by exploiting the flexibility of the HVAC system, MPC resulted in a reduction in building running costs as well as an improvement in power grid performance [140].

5.2. Uses of Optimization Algorithms in BEMS

In designing low-energy buildings, mathematical optimization can be used as a powerful tool to minimize the consumption of energy, while continuous and discrete issues are the two primary types of optimization challenges [141,142]. These problems can be formulated as binary, integer, or mixed integer optimization problems. Optimization algorithms are applied to solve these types of problems in various engineering fields [143].

A brief summary of the most selected optimization algorithms applied to BEMS problems is as follows:

5.2.1. Ant Colony Optimization (ACO)

ACO was motivated by observations of ant behavior [144]. This approach was originally created to handle discrete optimization problems before being expanded to include continuous variables. ACO for the continuous domain is the name of the extension (ACOR). ACOR showed better performance in finding the best solution as compared to other benchmark algorithms: particle swarm optimization with inertia weight (PSOIW), hybrid particle swarm optimization and Hooke–Jeeves (PSO-HJ), and the Nelder–Mead (NM) algorithm [142]. An ACO load scheduling strategy for a smart home was proposed. The goal was to achieve the best possible use of integrated renewable energy sources. This is accomplished by concentrating on the total electricity bill, TOU, and the overall improved quality of life (QoL) [145].

5.2.2. Artificial Bee Colony (ABC)

ABC is an optimization algorithm based on honey bee foraging behavior [146]. In [147], a HEMS for household appliances was proposed by implementing DR schemes for residential consumers with facilitating renewable energy integration. This framework was solved based on an improved ABC algorithm. In [148], the authors proposed a new approach of ABC with Knowledge Base (ABC-KB) for the management of power and the occupant's preferred environment inside a residential building. ABC-KB uses less power than GA and PSO.

5.2.3. Particle Swarm Optimization (PSO)

PSO is an optimization technique based on the social behavior of bird flocking or fish schooling [149]. The conventional continuous PSO algorithm was modified to binary spaces, while BPSO is a binary variant of PSO. It is a bird-inspired optimization technique based on flocks of birds looking for food. Birds move in certain locations and velocities when foraging for food [150]. In [151], they adopted and developed cooperative particle swarm optimization (CPSO) to optimize user comfort and the electricity bills of individual homes as well as avoiding peak loads and peak rebounds on the grid. In [152], they provided a regularized PSO algorithm for optimally controlling battery energy in a grid-connected microgrid, lowering power costs.

5.2.4. Genetic Algorithm (GA)

GA is an iterative optimization technique inspired by live creatures' genetic processes. New genes are created that inherit the characteristics of their parents [153]. Chromosome representation and algorithmic flows are the two main components of a GA. An algorithmic flow is an iterative technique for generating and evolutionarily selecting chromosomes to obtain high-quality solutions, while a chromosomal representation is a scheme for modeling a solution [154]. GA was used to optimize the scheduling of ESS and plug-in electric vehicle (PEV) operations in a home energy management strategy in order to reduce daily electrical energy expenditure for the user [155]. Residential load management solutions may necessitate appliance scheduling to achieve specific goals such as load factor reduction, a PAR ratio reduction, or energy cost reduction. This problem is solved using GA [156].

5.2.5. Other Optimization Algorithms

In [157], the proposed hybrid algorithms have better performance and faster convergence compared to a single-based algorithm. The hybrid-based algorithms such as bacterial foraging optimization (BFO), gray wolf optimization (GWO), wind-driven optimization (WDO), enhanced differential evolution (EDE), and the harmonic search (HS) algorithm can solve the DSM optimization problems in SG. A detailed summary of other optimization algorithms is illustrated in Table 1.

Table 1. Summary of others optimization approaches in BEMS.

Optimization Techniques	Objectives	Contributions	Ref.
HEDE based on EDE and HSA	Cost, PAR, and user comfort optimization.	EDE performance is better than HSA in terms of cost reduction and HSA is better in terms of PAR as compared to EDE.	[158]
Dijkstra algorithm (DA)	Consumption cost, curtailed loads, grid imbalances, and used energy mixes optimization.	DA reduced 51.72% of the cost when attaching RER and 10.22% of PAR.	[159]
Satin bowerbird optimization (SBO) algorithm	To optimize the scheduling of appliances within a discrete comfort window (DCW).	Reduced the electricity cost from ₹29.14/day to ₹22.84/day, and reduction of PAR is 10.28%.	[160]
Cuckoo search optimization (CSO) algorithm	Reduction in electricity cost, PAR, and minimum user waiting time.	CSOA is superior in terms of cost and PAR compared to CSA and GA.	[161]
Hybrid genetic particle swarm optimization (HGPO) algorithm	Optimization of electricity bills, carbon emissions, user comfort, PAR.	Reduction of electricity cost by 25.55%, PAR by 36.98, and carbon emissions by 24.02%, respectively.	[162]
Genetic BPSO (GBPSO) algorithm	Electricity bills and PAR optimization.	GBPSO is better in terms of both cost reduction and curtailment of PAR compared to GA, BPSO, WDO, and BFOA.	[163]
Binary backtracking search (BBS) algorithm	Reducing and scheduling energy usage.	BBSA provides better performance compared to BPSO, in terms of reducing energy consumption, total electricity bills, and saving the energy of certain loads at peak hours.	[164]
Harmony search gray wolf optimization (HSGWO) algorithm.	Efficient scheduling	HSGWO performs better than HSA and GWO in terms of cost and user comfort.	[165]

5.2.6. Neighborhood Energy Optimization Algorithms for a Set of Commercial Buildings

A single subject owns a number of the neighborhood's buildings in the single-owner scenario. The architecture for energy optimization is centralized in design. The neighborhood buildings are owned by various subjects in the multi-owner scenario, each of whom seeks to reduce their individual energy costs. The building owners additionally consent to provide flexibility to the entire neighborhood and run their own local generation and storage units in a coordinated manner to achieve neighborhood-level goals. The architecture for energy optimization is hierarchical. A centralized optimization for a single-owner neighborhood with a high level of transparency and a hierarchical two-level optimization for a neighborhood with multiple owners and a reduced level of transparency are two separate optimization algorithms. Additionally, in order to lower the neighborhood net load as viewed from the grid side and maintain the neighborhood pollution emissions below a predetermined threshold, the neighborhood energy optimization algorithms schedule the generation and storage equipment based on energy prices. It has been demonstrated that the use of flexible resources, such as thermal storage (related to thermal comfort levels) or electrical storage, enables one to pursue an economic goal while utilizing the flexibility of the local energy supply.

5.3. The Impact of Dual Optimization Techniques in BEMS for a Commercial Building

Building optimization problems are considered MILP problems that have been solved using MPC [117]. Intelligent controlling has been used to manage loads efficiently and an ANN strategy has been adopted to maintain a comfort zone in the building for the occupant, with an MILP scheduling technique to decay the peak demand of consumer [166]. An energy management agent (EMA) consists of an ANN and MPC for the modeling and optimization of building flexibility. The Monte Carlo Tree search-based planning and control was used to find the optimal policies with an ANN. The system can predict the demand for a day ahead and has a tiny prediction error [167]. The proposed system consisted of an ANN and MPC. In contrast, an ANN was used for renewable energy (i.e., solar and wind) forecasting and ensured the optimized usages of generated energy, and MPC is adopted for intelligent home control [168].

The ANN is used to accurately predict power consumption and indoor temperature selection by given weather, occupancy, and temperature setpoints as input. At the same time, a GA has been taken to adapt to the ANN to minimize energy consumption, and an optimization control strategy was assessed in case of the day ahead and MPC [169].

The uncertainty of environmental variables and users' preferences has been tackled using a data-driven machine-learning approach. Furthermore, a lifelong multitask framework was adopted to exploit structural similarities in control policies as there were different room sizes in buildings. Kernel-based learning was pursued as well to mitigate the non-linearity policy. Finally, a dual decomposition method was employed to cope with DR constraints across the spaces, transforming the overall problem into a series of unconstrained stochastic optimization problems for individual rooms. The method was verified via numerical experimental based on semi-real data sets [170].

Three artificial intelligence techniques were used to solve the problem of energy demand planning in smart homes. First, the modification of the elitist none-dominated sorting genetic algorithm II to demand-side management was applied and accounted for electricity fluctuations over time, priority in the use of equipment, operating cycles, and a battery bank. Second, the forecast of demand-side consumers, distribution generation, renewable energies, and weather for a day ahead from the nearest meteorology office was considered for demand-side management by employing the SVR technique. Third, the k determined user comfort levels through the cluster technique [171]. Table 2 shows a full explanation of each optimization control technique, along with its benefits and drawbacks.

5.4. The Impact of Dual Optimization Techniques in BEMS for a Set of Commercial Buildings

Neighborhoods or districts are not frequently included in the application of optimum control ideas to achieve energy efficiency in buildings and the optimal exploitation of regional resources. In [171], they consider a neighborhood with several buildings that have agreed to coordinate how they use their energy loads and resources in order to achieve some overall objectives, while still allowing for the pursuit of individual optimization goals. When this occurs, a building's local resources should work together with a top-level optimization engine to balance the accomplishment of local optimization goals with neighborhood-level goals. A hierarchical optimization algorithm was introduced to divide the optimization at the building level and the neighborhood level in such a way that the bottom level managed the individual building objectives and the top level addressed the neighborhood-level objective, in order to address the most general case of multiple ownership neighborhoods. In particular, the building-level energy management would give the top-level optimizer flexibility and provide recommendations on control measures to implement to move the neighborhood closer to achieving its objectives [172]. The optimistic assumption in bilevel optimization (i.e., the two layers of optimization tasks are nested one inside the other) states that the consumers choose the best option that benefits the retailer the most. The pessimistic variant, on the other hand, deals with the scenario in which the consumers give the retailer their least preferred optimal response, protecting against potential losses brought on by an unexpected choice. However, the work in [173] shows the formal properties of the best solutions to a bilevel tariff optimization issue for both the computationally challenging general case with an arbitrary number of consumers and the particular case with an easily tractable single consumer. The key relevance of these findings is that by perturbing the issue data and the optimal price vector, the pessimistic variant may be reduced to the optimistic one, which also yields the first effective solution technique for the pessimistic version. On the other hand, a numerical case study was offered to show that, if consumers do not select their optimal solution as expected, addressing the optimistic problem could directly result in a significant loss of profit for the retailer. In [174], they emphasize the distinction between the optimistic and pessimistic versions of the bilevel optimization problem with regard to energy management.

Table 2. A comparison of the most commonly used optimization methods in BEMS.

Ref.	Control Techniques	Benefits	Drawbacks	Observations
[9]	Internet of Energy (IoE)	Maximizing energy efficiency by minimizing losses and environmental impact using IoE.	The requirement of big data processing and large storage.	21% of energy loads can be deducted with significant cost reduction and energy saving.
[11]	Combination of machine-learning and model-based control approach.	Considered all physical characteristics of the building and human comfort compared to other researchers.	There is no real implementation and performance of the proposed system, which is only comparable to theoretical ideas.	Reduces the consumption of energy by 8–18%.
[117]	DDQN	An aggregation controller has been used which aggregates all ILs in the system and remotely reads and interrupts the ILs.	There is less consideration of user preferences and comfort satisfaction.	Decreases the operating cost by 16.9% in a day.
[118]	ANN and MILP	Smart controlling to manage the loads efficiently.	Longer computation time.	Reduction of up to 12.5% of energy consumption and 10% improvement in peak demand.
[119]	MILP with PV and ESS	During 90% of the peak tariff, consumers can sell electricity to the grid.	If all consumers were motivated to buy in the same period, the demand may have increased dramatically.	Reducing the flexible loads by 40% while saving 30% of overall costs.
[124]	Rule-based algorithm	Strong control reliability and system reduces significant power.	The number of people detected in the room and consumption rate are not considered.	Savings of 23.5 kWh and USD 2.898 in total daily energy consumption.
[137]	DANN	Synthetic load profile generator is a robust and adaptable solution.	Slow convergence and longer computational time.	Achieved an average RMSE value of 111W and coefficient of determination is 97.5%.
[138]	QL-PLR using RL	Higher convergence rate.	Consumer preference was not prioritized.	The system can reduce peak load demand by 9.28%.
[167]	ANN and MPC	The next-day electricity price is provided to EMA to optimize the energy cost by controlling the heat pump.	There is a variation that may introduce the disturbance of human comfort.	Reduces energy costs by 14.8%, when only heat pumps are used.
[168]	ANN and MPC	Provides good forecasting results compared to real assumptions with fewer error percentages.	The system will be required to investigate variable loads.	The system can sell energy to the grid for EGP 3.2 (Egyptian pound) within one day.
[169]	GA, ANN, and MPC	When loads are shifted within TOU, the results of energy savings increase by 27%.	The authors have considered 100% accurate forecasting which is not possible in a real scenario.	A total of 25% energy savings.
[171]	Flexibility envelop concept and MPC	The MPC-based schemes increase the self-sufficiency of buildings.	No consideration of any forecasting error which is impossible in real cases.	16% cost savings and 10% emission savings in the winter season, whereas in the summer, they were 26% and 29%, respectively.
[172]	MILP and MPC	Attempt to maintain energy consumption below the expected consumption for purpose of balancing.	HVAC model was out of the present work.	Saves approximately 125 KWh of net energy.
[173]	MG-EMS	Scalability, reliability, and extensibility.	It is implemented for residential use as one room at a time able to connect with solar energy.	The main power grid's peak energy demand is reduced by 30.6%.
[174]	EMS-in-Bs	Each function is critically synthesized by sub-function.	There is no clear direction in which methods might be preferable for BEMS.	"Control-optimize" achieves the highest energy saving rates of around 30% compared to "estimate-predict" with 10%.

6. Future Trends and Issues

Most high-rise buildings are constructed in city/urban areas rather than rural areas where there is an increased density of buildings and no outer space to use the solar energy. The following are future trends and issues which may have the potential to increase the building energy efficiency for both existing and new buildings.

6.1. Building Integrated Photovoltaics (BIPVs)

The current global power demand is roughly 15 Tera Watt (15×10^4 W), or 10^4 times less than solar power incidents on the earth. The solar energy received in less than an hour is thought to be enough to cover a year's worth of the global energy budget [175]. Therefore, photovoltaic (PV) technology is one of the most attractive options for making efficient use of solar energy. BIPVs are photovoltaic modules that are incorporated into the building envelope, therefore replacing the traditional components of the building envelope. PV modules are used as roofs, facades, and skylights in this application. In comparison to non-integrated systems, BIPVs have a significant benefit because land allocation and stand-alone PV systems are not required [176]. Photovoltaic foils, photovoltaic tiles, photovoltaic modules, and solar cell glazing are some of the different types of BIPV buildings, as shown in Figures 8 and 9, respectively, that use BIPV technology to become energy producers rather than consumers.

The advancement of BIPV technology and its incorporation into the building envelope provides aesthetic, economic, and technical benefits [175]. BIPV systems can be a powerful and versatile tool to meet the increasing demand for zero energy and zero emission buildings in the near future [177]. BIPVs are capable of delivering electricity at less than the cost of grid-connected electricity to end users at certain peak demand, which may lead to peak shaving without compromising human comfort [178].

Weather protection, thermal insulation, noise reduction, heating and cooling load reduction, and other benefits are all provided by the BIPV [179,180]. Utilizing a BIPV semi-transparent arrangement, some of the sunlight can be used for day illumination inside the building [181]. Due to the scarcity of ground area and the abundance of underutilized roof space, rooftop solar PV systems are gaining popularity, resulting in the prediction that the BIPV industry will increase rapidly soon [182]. In addition, feed-in tariffs (FiTs) and other government-sponsored solar energy programs have gained widespread acceptability around the world. Sanyo, Schott Solar, Sharp, and Sun-tech are among the firms developing innovative BIPV technologies for façades, skylights, and windows. FiT implementation, public acceptance, government economic support in the form of subsidies, and technical elements such as power losses and architectural concerns are the most significant impediments to BIPV system adoption [183]. However, a BIPV system's power-generating efficiency is lower than that of stand-alone and BIPV/T systems, but it eliminates the need for an additional power-generation space [184]. Overall, due to its functional qualities, this technology has a promising future in the coming years.

6.2. Net Zero Energy Building Concepts

The primary enabler of a future smart building is the energy performance of buildings, which leads to energy flexibility, generation, and interaction between users. Energy retrofitting for net-zero energy buildings (NZEBs), in conjunction with passive control strategies, energy-efficient technologies, and RER integration, creates a balance between demand and generation while also taking grid integration into account. Smart home energy retrofitting strategies are adapted for the improvement of existing buildings along with key performance indicators for measuring the performance and success of acquiring sustainability in intelligent buildings [188]. A ZEB or NZEB implies the integration of renewable resources if weighted supply and weighted demand are equal to zero, focusing on energy storage systems and materials, energy routers, renewable resources, and plug-and-play interfaces [9,11]. In addition, an NZEB is a preferred sustainable building style since it can meet its own energy needs while also producing surplus energy to feed into the grid.

However, NZEBs are involved in more energy-related systems and grid linkages, and their energy systems are more intricate than in conventional buildings [189].

Figure 8. Available BIPV systems on the market [185].

(**a**) (**b**)

Figure 9. (**a**) BIPV façades powered by electricity to assist natural ventilation [186]; (**b**) an entrance with a PV skylight [187].

In [188], the EU adopted long-term goals to reduce 80–95% of carbon by 2050, where existing buildings will require a renovation rate greater than 3% per year in 2050 to achieve decarbonization. In addition, the occupant's behavior variation may lead to a 40% change in energy usage [11]. The UK was the first country to mandate NZEBs on a large scale in 2016 and France followed in 2020. The EU announced plans to initiate NZEBs in January 2021, and the US Department of Energy (DOE) targeted marketable zero-energy homes in 2020, followed by commercial zero-energy buildings in 2025. Other than that, ASHRAE (American Society of Heating, Refrigeration and Air-conditioning Engineers) plans to customize NZEBs in 2030, as shown in Figure 10. Moreover, Denmark has shown 100% renewable energy usage for heating and cooling systems [190].

In new and existing buildings, for example, it is possible to achieve total energy savings of 20%. Significant energy savings for cooling can be achieved by reducing external loads with proper building façade shading, reducing internal loads from lighting with energy-efficient fluorescent lamps, and using natural cooling techniques such as ground, evaporative, and radiative cooling, as well as night ventilation [24].

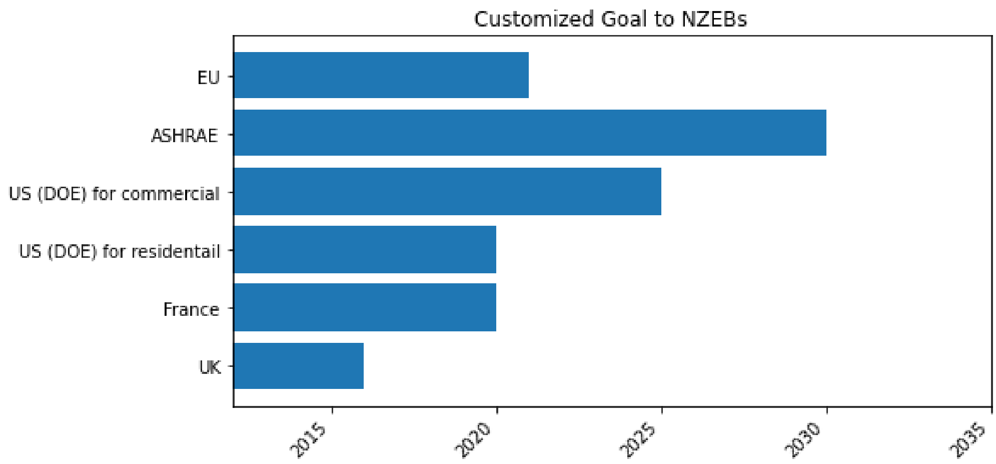

Figure 10. The aim of countries is to customize NZEBs over the years.

In [191], the authors presented a unique yet viable and cost-effective method for advancing the state-of-the-art of smart energy buildings and achieving the real meaning of net-zero energy buildings. The proposed solution consisted of new trigeneration solar collectors without a battery, a highly creative form of heat pump integration that needed minimal size and expense, and the two-way interaction of a building with local energy networks. A zero-energy building is self-sufficient in terms of energy use, producing as much as it consumes. In ZEBs, both passive and active design methods were used to minimize energy consumption, with renewable energy strategies (mostly solar panels) used to meet demand following the reduction [192].

A study was conducted to investigate ZEBs in Southeast Asia, which was adapted from an existing structure and used a variety of passive and active design solutions appropriate for a tropical climate. According to the research findings, active and passive measures should be incorporated into building design to improve energy efficiency. Passive design, in particular, must be used on a broad scale in order to achieve significant energy savings [74]. The combination of active and passive design solutions toward ZEBs are shown in Table 3.

Table 3. Strategies of energy efficient retrofitting for ZEB.

	Domain Area	Achieving Strategies of Energy Efficiency Using Retrofitting	Ref.
Passive design solution	1. Prevention of heat gains and losses	• Conduction heat gains through the walls and roofs can be reduced by implementing insulation or both sides of the walls and roofs can be polished or coated using colors. • Those materials that have higher thermal resistivity can be selected. • Solar radiation through window glasses can be minimized up to 75%, by having two or more layers, and inside, between them, will be dead air. • Using localized treatment can make an outstanding contribution to reducing heat gains, such as shading, modification lighting, removal of machines from conditioned space, etc. • Pre-heating and pre-cooling can be adopted before occupying the conditioned area. • Green roofs and green walls are highly efficient in managing cooling loads.	[23,25,48,193–195]
	2. Increased natural ventilation	• Natural ventilation with solar assistance.	[74,196]
	3. Enhanced daylight	• Mirror ducts • Lights shelves • Light pipes • Skylights	[74,197]

Table 3. *Cont.*

	Domain Area	Achieving Strategies of Energy Efficiency Using Retrofitting	Ref.
Active design solutions	1. Correct system design	• The design should take into account the operational circumstances that occur over the majority of the running hours. Optimization under these conditions will be more beneficial than calculation at a single extreme design point.	[23,25,198]
	2. Control philosophy	• To guarantee low condensing temperatures are available during the part load operation, avoid fixed set head pressure control. • Auxiliaries pump with set speeds can be avoided if possible, and fan power should be lowered at low loads. • Ensure that defrosting is only used when absolutely necessary and that it is completed as effectively as possible.	
	3. Optimize components	• Compressor and condensing units should be selected at normal running conditions. • Evaporator unit and temperature selection can be appointed based on human activities. • Temperature differences must be considered for the choice of heat exchangers. • Choose the appropriate refrigerant for application. If all other design parameters are optimized, the refrigerant's impact on efficiency is expected to be less than 5%.	
	4. Proper installation	• Following the guidance of the manufacturers for installation, such as maintaining the distance between indoor and outdoor units, leveling between them, and providing adequate space for air circulation to heat reject and absorb. • It is required to have an accurate amount of gas charge that ensures no over- and undercharging. • Correct adjustment of the expansion valve.	
	5. Operation and maintenance	• No secondary flow problem. • Ensure the cleanliness of filters, coils, and other components. • If all installed systems are operating correctly, it can be estimated that an average of 10% energy savings can be achieved, reducing running costs.	
	6. Energy efficiency lighting	• LED • Task lights • Dimmers • Sensors	[102,199–201]
	7. Intelligent BEMS	Building energy management System	[86,118,202]
	8. BESS	Battery energy storage system	[203–205]
	9. Renewable energy integration	Solar panels and wind turbines	[74,118,206]

6.3. Demand Control Ventilation (DCV)

Commercial building ventilation is required to remove the airborne contaminants generated by occupants' and other living organisms' biological functions, occupant tasks and operations, equipment, supplies and furnishings, building materials, and the products of chemical reactions between contaminants from both indoor and outdoor sources [207]. Fisk [208] estimated that improving interior environmental conditions in commercial buildings might save USD tens of billions per year in the US. One of the few important elements required for these improvements was adequate ventilation. In nearly all U.S. climates, building HVAC systems require a large amount of energy to condition the external air utilized for ventilation. Natural ventilation, mechanical ventilation, or a combination of the two, referred to as hybrid ventilation, are examples of different types of ventilation systems [209]. In addition, there are also two types of ventilation airflow that can be supplied to the room by using constant air volume (CAV) or variable air volume (VAV). In industrial, commercial, educational, and office buildings, the VAV system is already widely used [210].

Several researchers have examined the effects of outdoor air supply rates (i.e., ventilation rates) on human health, comfort, and performance in commercial buildings. Lower rates of sick leave and the incidence of common respiratory disorders are linked to higher ventilation rates. Lower ventilation rates have been associated with building-related sickness (BRI), sometimes referred to as sick building syndrome (SBS). By adapting the ventilation air conditioning load to the actual occupancy, DCV can save energy. During this time, a variety of occupancy measurements were considered, including carbon dioxide (CO_2), volatile organic compound (VOC), and humidity concentrations [211].

It is important to have adequate ventilation since it protects our health as well as our buildings. However, the ventilation and energy needed for optimal indoor air quality (IAQ) may conflict [212]. Therefore, one of the most energy-efficient ways to obtain the best IAQ is to use DCV. As shown in Figure 11 [213], DCV is a typical concept in HVAC systems that uses signals from inside sensors to continuously match the ventilation airflow rate with the actual demand. Likewise, DCV refers to the control of mechanically supplied rates of external air intake into buildings based on occupant demand. A HVAC system is typically built and operated to keep the ideal environmental conditions in place in order to maintain acceptable thermal comfort and IAQ. In a recently constructed Swedish building, the effects of VAV ventilation on IAQ and the potential for energy savings were investigated. The VAV system can more efficiently satisfy thermal comfort requirements while using less energy than a CAV system. A VAV system combined with the DCV approach has become one of the most energy-efficient ways to ensure both optimal IAQ and thermal comfort as the DCV idea has evolved [214].

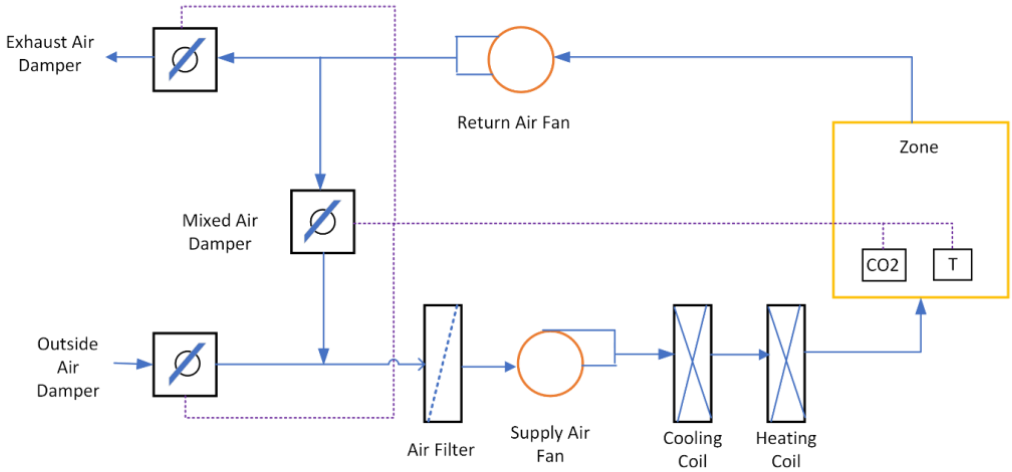

Figure 11. A typical view of demand control ventilation (DCV) [213].

In [212], research on a multi-residential complex examines the energy-saving possibilities of a ventilation system with an air-cleaning unit and demand control. This method is based on the need to save energy in ventilation by limiting the supply of outdoor air while maintaining the desired air quality by using air cleaning. As a result, in this study, the ventilation system's operation mode detects indoor CO_2 and formaldehyde (HCHO) concentrations in accordance with the IAQ standards for Korean dwellings. IAQ has recently gained prominence as a means of addressing specific occupant health and safety concerns.

To overcome the multi-zone demand-controlled ventilation system's over-ventilation and under-ventilation concerns, an air balancing method was developed. Increased energy efficiency has become a primary priority for the future accomplishment of zero usage in buildings. A mechanical ventilation system, which operates on a 12-month basis, is one of the most energy-intensive systems in HVAC. This suggests that lowering the airflow rates can save a lot of energy by reducing the fan's energy consumption and heating/cooling the supplied air [28]. As a result, it is suggested to investigate a building's ventilation system's energy-saving possibilities.

In [215], they proposed the integration of a two-level distributed method with an upper and lower-level control, where the upper level calculates zone mass flow rates to keep zone thermal comfort (TC) at a low cost of energy, and the bottom level strategically manages zone mass flow rates and ventilation rates to accomplish IAQ in conjunction with retaining higher levels of near-energy-saving performance. The results of certain studies have shown that the DCV technique has the potential to conserve energy, particularly in buildings with a high occupancy density [216,217].

6.4. Integrating SDG Goals

The UN presented 17 SDGs in 2015, with the goal of providing a common vision in terms of good living and a peaceful environment for this world and its people [218]. We investigated several studies to see if there was a link between BEMS and the SDG targets. We have found the importance of an IEMS's capability to achieve the UN SDGs. It shows that the improvement of a building's energy efficiency, by using the greater control and optimization of energy management with renewable energy resources, is thereby able to acquire three aspects of sustainability: social, economic, and environmental, all of which have a strong association with 7 out of the 17 SDGs [219], as shown in Table 4.

Table 4. BEMS helping to achieve the SDGs.

Domain		Goal	BEMS in the Pursuit of the SDGs	Ref.
Social	3 GOOD HEALTH AND WELL-BEING	Ensure healthy lives for all ages and promote well-being.	• A smart building with the integration of an optimization controller which provides features such as thermal, humidity, and visual temperature comfort, alongside being able to reduce a significant amount of energy consumption, also results in less air pollution and emissions which creates healthy lives and well-being for inhabitants of a city.	[134,135,220]
	7 AFFORDABLE AND CLEAN ENERGY	Ensure that everyone has access to inexpensive, modern energy.	• To achieve affordable and modern energy using BEMS with the inclusion of optimization control strategies, RER, and ESS to become more cost-effective than fossil fuel alternatives.	[220–222]
	11 SUSTAINABLE CITIES AND COMMUNITIES	Ensures that cities and human settlements are inclusive, safe, resilient, and long-lasting.	• BEMS' concept, design, and technology can be used to create sustainable metropolitan cities and communities by reducing energy usage.	[105,220]
Economic	8 DECENT WORK AND ECONOMIC GROWTH	Foster inclusive, long-term economic growth, full and productive employment, and decent work for all.	• The demand for smart buildings is growing, and as a result, the manufacturing of diverse BEMS components demands a large workforce, creating opportunities for green jobs that lead to long-term economic growth.	[220,223]
	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE	Build more resilient infrastructure, encourage inclusive and sustainable industrialization, and cheer on innovation.	• BEMS' optimization and control make building infrastructure more sustainable, resilient, and adaptable to changing global climate circumstances, allowing for economic success.	[220,224,225]
	12 RESPONSIBLE CONSUMPTION AND PRODUCTION	Ensure that consumption and production trends are long-term.	• In the form of microgrids, distributed power generation, smart grids, and virtual power plants, energy management in a smart building with proper controllers and optimization ensures a proper supply–load trade-off.	[220,226]

Table 4. *Cont.*

Domain		Goal	BEMS in the Pursuit of the SDGs	Ref.
Environment		Take immediate action to address climate change and its effects.	• Using various RER combined with intelligent controllers in BEMS, the impact of carbon emissions on climate change can be reduced.	[220,227]

6.5. Data Privacy and Security

For communication between appliances and the end-user in a smart house, various wireless communication technologies have been introduced. Smart building appliances are connected to a wireless control network such as ZigBee, Bluetooth, or Wi-Fi to receive and send commands remotely or automatically. The IEEE 802.11 (Wi-Fi), IEEE 802.16 (WiMAX), IEEE 802.15.1 (Bluetooth), and IEEE 802.15.4 (Zigbee) standards are the most widely used wireless technologies in smart homes [228]. Two types of communication protocols are usually used in IoT-enabled smart infrastructure: Zigbee for device-to-device communication and Wi-Fi for device-to-AMI connectivity [105]. A brief comparison of wireless communication protocols used in HEMS is presented in Table 5.

Table 5. Comparison of different wireless communication technologies for the smart home.

Technology	Spectrum	Data Rate	Coverage Range	Applications	Limitations	Power Consumption
Wi-Fi	2.4–5 GHZ	Up to 300 Mbps	100–300 m	Monitoring and controlling	Interference and security	Very High
Bluetooth	2.4 GHZ	1 Mbps	10 m	Device to device	Low data speed, short range, poor data security	Low
Zigbee	2.4 GHZ	250 Kbps	30–40 m	Device to device	Low data speed and short range	Very low
WiMAX	2–11 GHZ	Up to 70 Mbps	8–50 Km	AMI, Demand response	Lack of quality and interference	Much higher
5G	1–6 GHZ	Up to 10 Gbps	About 1000 ft	AMI, Demand response	Privacy and security	Very much higher

The emergence of intelligent cities in the world is encountered chiefly to preserve the privacy and security of data involving big data analytics. Without the authorization of the owner's privacy, accessing data generated in smart cities will not be legal. In this case, personal data acquisition can be encouraged to motivate data owners by promoting incentives via an intelligent contract that provides privacy. Estonia introduced the world's first "data embassy" which can be operated from data centers outside of Estonia for reliable operation and to restrict potential cyber-attacks [229].

On top of this, the unveiling of the new innovative technology called blockchain is now the key to the data-driven world. The usage of blockchains is booming rapidly, with a market size of USD 3 billion to 39.7 billion by 2025 [1]. The integration of the constrained application protocol (CoAP) for the sending and receiving of data in IoT systems minimizes the power consumption of IoT devices with datagram transport layer protection (DTLS) security and the usage of CoAP in the intelligent building. However, that is less than the message queuing telemetry transport case (MQTT). The aim is to integrate the DTLS protocol with the secure hash algorithm (SHA-256) using optimization to improve security [230].

The essential features of blockchain are seamless authentication, privacy, security, effortless deployment, and maintenance. Smart cities are required to modernize their buildings by implementing home automation with decarbonization and improved consumer security and privacy. The demonstration focuses on future energy management research by highlighting the key emerging areas, namely context-aware energy management, energy management for smart homes and grids, and the role of privacy preservation in IEMS. One paper addressed the technical challenges and possible solutions for their implementation in IEMS and also summarized the future perspectives to make the system more reliable, robust, and customized [231]. The problems in the centralized architecture of intelligent building energy management systems (IBEMS) are, namely, the difficulty of networking between end devices, the lack of flexibility, and the limited sharing of underlying information. The analysis of the formulation of a wireless sensor network (WSN) for the power supply, distribution management system, and design of a network model of the IBEMS can overcome these problems. For the security purposes of the IBEMS, a blockchain-based dynamic key management strategy was proposed, and experimental results show the reduction of data storage time and the space of sensors, which optimizes the control of the IBEMS. Moreover, research results assist in promoting blockchain technology in the scenario of Ubiquitous Power Internet of Things (UPIoT) [232]. To make a smart city where the whole area has to be digitalized by placing sensors everywhere, namely transport, e-health, agriculture, and so on, care must be taken with data privacy and security [112].

6.6. Emerging Energy Policies

At present, increasing the concentration on imposing energy policies to maximize efficiency with the minimization of generation costs alongside occupant comfort is necessary. Ensuring the proper utilization of energy requires an energy audit to analyze and compare them. The energy policy of the DSM must have objectives for emission reduction, energy security, affordability, and encompass energy efficiency, demand response, one-site backup generation, and storage [233,234].

Moreover, the energy policy in peninsular Malaysia, by proposing the enhanced time of use (ETOU), has a subsection of the time-based program by including TOU (enlarged to ETOU), off-peak tariff rider (OPTR), and Sunday tariff rider (STR). The authors illustrated that electricity bills are about 0.5% to 12% higher due to improper implementation of load management (LM) and DSM during ETOU tariff shafting [235]. The proposed strategy formulation has been demonstrated to DSM in order for valley filling, load clapping, and load shifting to be implemented. The major commercial and industrial consumers must be persuaded to use approximately 20–50% of LM based on a price-based program (PBP) [235]. DSM strategies motivate consumers to shift their loads to optimize energy usage—the motivation is based on two DR classifications, namely incentive and price-based. Whereas three control techniques have been proposed, namely passive, active, and transactive, only transactive controllers have bidirectional communication, allowing end-user loads to bid on their demand. The price is set based on the buyers' and sellers' bids [236].

According to the report [117], the guidance of energy traders to design cost-effective and efficient IEMS and system architecture consists of an admission controller (AC), a load balancer (LB), and a third layer composed of a demand response manager (DRM) and load forecaster (LF). Two-way demand response manager communication receives the critical peak pricing (CCP), TOU, and real-time pricing with predicted demand from load forecaster. Afterward, the available capacity is found by the admission controller and then allowed to appliances, otherwise rejecting again to LB, and that is the way to create a balance between the reduction of the valley falling and load shafting, and make the load consumption shape stable. A detailed summary of the energy policy is shown in Table 6.

Table 6. Energy policy to demand side management.

Ref.	Country	Programs	Challenges	Remarks
[235]	Malaysia	• Mid peak time has been implanted in time zone segmentation that consists of 10 h while peak time segmentation is reduced to 4 h. • If anyone is registering under the Sunday tariff rider, the charge for maximum demand (MD) rate by TNB is not considered. • Some specific categories of domestic and commercial consumers receive a discount up to 10%, and domestic consumers whose electricity demands are under 300 kWh will also be eligible for an exemption of 6% service tax.	• Motivating consumers requires a significant amount of effort.	• Consumers and power plants are correlated. Therefore, energy implementation policies must also address consumers' comfort.
[237–239]	UK, EU	• To stimulate the development of energy labeling, product standards, and certification of appliances and equipment through the EU's energy labeling framework and the eco-design directive. • Balance mechanism during peak time by usage of backup generation, cross-border interconnection, storage, and DSM.	• It requires consensus between utility authorities and consumers or neighboring countries for cross-border inter-connection.	• Inspiring consumers through incentive-based load scheduling along with the adoption of smart control and monitoring.
[240]		• DSM has been categorized into energy efficiency (EE), TOU, market DR, physical DR, spinning reserve (SR), and these are correlated with smart energy control policy.	• It necessitates an incentive for agreement between utility providers and consumers.	• It can also encourage the adoption of RER and ESS.
[241]		• The policies of ESS are proposed to manage renewable energy integration and grid stability. • ESS can also be used for power backup and energy arbitrage.	• It will have a larger investment and maintenance cost.	• ESS is being adopted in developed countries rather than developing countries, as they have the ability to afford it and the expertise.
[242]	Bangladesh	• Efficiency improvement of home appliances and energy saving behavior in the residential sector would reduce consumption by about 50.7%, as shown in the Energy Efficiency and Conservation Master Plan (EECMP) of Bangladesh.	• It has the limitations of the existing technology in the developing world.	• Inspiring best practices of energy-saving behavior using print media and social networking.
[243]	Singapore	• The three main DSM strategies in Singapore are the TOU price, real-time price, and direct DR program.	• There is no linearity that might affect the consumer.	• Rooftop solar, ESS, and real-time load control can be implemented for DSM.
[244]	USA	• Using a battery is a promising solution to mitigate peak demand under a real-life tariff model in New York City.	• A longer payback period can create barriers for a wide scale of adaption.	• It can be developed based on a battery's life cycle cost assessment and degradation cost of the battery.
[245]	Kuwait	• Incentive-based demand response programs can be considered in Kuwait.	• It is dependent on the consumer consensus. • Existing electric grid requires upgrading to a smart grid.	• Solar energy and batteries can be emerging solutions to DSM in Kuwait.
[246,247]	China	• In 2015, the central government of China provided 100 CNY/kWh for temporary peak load reduction using incentive-based DR in Beijing, Jiangsu, and Foshan provinces.	• Incentives are not enough to recover the cost of shifting and reducing loads.	• The power sector of China can be reformed by increasing the integration of renewable energy on both the generation and demand sides.

Table 6. *Cont.*

Ref.	Country	Programs	Challenges	Remarks
[248]	India	▪ Highly concentrated on peak reduction in DSM programs in India, whereas agriculture and small-scale industries are heavily subsidized. National electricity policy also emphasizes periodic energy audits, labeling, and standardization of appliances for voluntary and self-regulatory initiatives.	▪ Several obstacles are impeding the implementation of DSM programs, and these obstacles must be identified and overcome for India's DSM potential to be fully realized.	▪ However, such rules must be updated, and regulatory mechanisms must be developed to encourage utility companies to implement DSM programs on a greater scale.
[249]	South Africa	▪ The adoption of dynamic pricing for 100% household participation saves roughly ZAR 3,115,047 per day compared to TOU pricing in South Africa. ▪ DSM has been found to alleviate poverty by lowering household power expenses by 1.2%, 1.5%, and 2.9% on a monthly basis for households with 100%, 50%, and 30% involvement, respectively.	▪ The fact that pseudo-peaks could be formed during periods of lower electricity rates, which could disrupt grid operation if demand exceeds supply capacity, is a disadvantage of using the TOU pricing structure.	▪ In South Africa, there is a potential opportunity for solar energy on both the supply and demand sides.
[250]	Brazil	▪ To encourage peak load reduction in Brazil, a set of levies was created for large consumers. To do so, consumers were divided into two categories: consumers with high voltage access and low-voltage-access consumers. ▪ Both tariffs are intended to reduce peak load consumption by moving load to off-peak hours or replacing generation.	▪ The main problem with these schemes for large consumers is that they may have inflexible loads during peak periods which encourage the consumers to have self-generation using fossil fuels.	▪ DSM treatments may create some consumer dissatisfaction, necessitating habit modifications in people who are affected.
[251]	Australia	▪ Australia promotes demand-side opportunities by focusing on improving energy efficiency, the substitution of energy sources, load shifting, and peak shaving.	▪ To overcome the lack of consumer acceptance, awareness, and technical barriers to DSM.	▪ The consumer's preference must be prioritized.
[252,253]	Thailand	▪ In Thailand, from 2003–2017, the use of energy efficiency programs and efficient power generation technologies would reduce CO2 by 8.4%.	▪ High investment costs.	▪ Price- or incentive-based tariffs can be adopted.
[254]	Indonesia	▪ Indonesia will reduce electricity demand by 5.2% in 2025 using lighting efficiency improvements in Java–Madura–Bali (Jamali) Islands.	▪ Less public awareness, financial limitations.	▪ It might be achieved if it receives support from the Indonesian government and the people.

7. Discussion and Conclusions

Following existing main issues in current research on BEMS, the corresponding suggestions are given, which can stimulate further research.

- Finding the best location for PV installation in terms of building density may not be optimal for mutual occlusion, reflecting the congestion of buildings in urban areas. Hence, BIPV technology can be implemented in buildings. In addition, it is required to focus on monitoring and controlling loads in real-time to save the significant energy consumption deliberately wasted by human behavior, along with an increasing awareness of energy utilization.
- Many researchers discussed the application of the IoE to BEMS but did not mention the assessment of cyber-attacks with an increasing threat to national security. Therefore, further studies can be conducted for multi-storied buildings because there will be many sub-controllers based on the central controller, handling large amounts of data to preserve privacy and security.
- An in-depth investigation is required to optimize the IEMS according to occupant comfort, considering all indoor air comfort index parameters such as thermal, visual, acoustic, and air quality properties.
- Many authors provided an overview of artificial intelligence (AI) and deep learning techniques, whereas they did not provide the outline of the best configuration in terms

of computational time and error in BEMS. More research is required to profoundly improve the performance of optimization algorithms with less computation time and error that might respond accordingly to consumer needs over time.

- Passive design solutions are undeniably important for reducing energy use and improving human comfort. Many green architects use passive design as part of their sustainable design strategy. However, because of temperature and density, passive design should be cautiously applied in existing building retrofits in hot–humid climates with crowded urban environments, taking into account cost and effectiveness [74].
- As renewable energies are intermittent, more emphasis should be given to finding the optimum sizing of RER and battery storage to minimize the initial and maintenance costs, which is the key way to approaching consumers for the encouragement of adopting BEMS.

This review paper has comprehensively extracted the contribution of BEMS to curtail load profile with optimization control, by introducing energy policies. As a result, significant energy savings may lead to sustained initiative, and the installation of new power plants, as an emerging technology that can perform decarbonization in an intelligent building with the optimization of self-generation and self-scheduling, and introduction of the prosumer. However, the impact of optimizing building energy management on SDGs must also be assessed as SDGs address global concerns. Building energy-saving strategies can save a significant amount of energy, which is beneficial to reducing a building's negative environmental effects and enhancing its sustainability. Therefore, the primary data, findings, analysis, and recommendations gleaned from this evaluation could be quite useful in building and implementing an optimum controller in the case of BEMS to design energy-efficient buildings.

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