sustainability

Review

Balancing Sustainability and Comfort: A Holistic Study of Building Control Strategies That Meet the Global Standards for Efficiency and Thermal Comfort

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Abstract: The objective of energy transition is to convert the worldwide energy sector from using fossil fuels to using sources that do not emit carbon by the end of the current century. In order to achieve sustainability in the construction of energy-positive buildings, it is crucial to employ novel approaches to reduce reliance on fossil fuels. Hence, it is essential to develop buildings with very efficient structures to promote sustainable energy practices and minimize the environmental impact. Our aims were to shed some light on the standards, building modeling strategies, and recent advances regarding the methods of control utilized in the building sector and to pinpoint the areas for improvement in the methods of control in buildings in hopes of giving future scholars a clearer understanding of the issues that need to be addressed. Accordingly, we focused on recent works that handle methods of control in buildings, which we filtered based on their approaches and relevance to the subject at hand. Furthermore, we ran a critical analysis of the reviewed works. Our work proves that model predictive control (MPC) is the most commonly used among other methods in combination with AI. However, it still faces some challenges, especially regarding its complexity.

Keywords: MPC; building energy efficiency; control techniques; modeling; thermal comfort

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1. Introduction

For centuries, nations survived on fossil fuel exploitation as a main source of energy to power vehicles and enhance residential comfort, among other things. For instance, fossil fuels such as oil, coal, and gas have been at the core of industries since the 1700s [1,2]. Ever since, fossil fuels have been integrated in almost every aspect of human lives, including heating, transportation, and in residential activities, among others.

A significant turning point occurred during the second industrial revolution, known as Industry 2.0, with the discovery of electricity [2,3]. Industrial and residential activities became more ferocious, as electricity helped make industrial processes easier. For example, electricity was used to power air conditioners for indoor heating instead of burning wood and/or charcoal [4]. The consumption of electricity in the industrial and transportation sectors has seen substantial growth since the industrial revolution [4], which introduced new technologies such as the telegraph and combustion engines. These innovations laid the groundwork for electricity to become the primary source of power. While the primary goal of these technological advancements has been to enhance the comfort and efficiency of our living environments, it is essential to recognize the flip side of this evolution: the rising costs associated with increased electricity consumption. Furthermore, despite introducing electricity to the mainstream, fossil fuels were the main source of energy, and were also used to produce electricity itself [5].

The intense dependence on fossil fuels increased the concentrations of greenhouse gases in the atmosphere as result of industrial emissions. Coupled with the excessive exploitation of natural resources, planet earth started battling a new challenge known as climate change [6]. This phenomenon manifested itself through hurricanes, floods, heat waves, and forest fires caused by the rising temperature of the planet. As a result, 3.6 billion people currently live in challenging situations because of climate change [7] and its effects. Moreover, the insatiable use of natural resources in different industries over the years has driven these resources to the point of depletion [8,9]. For instance, in 2021, fossil fuels accounted for around 81% of total greenhouse gas emissions in the United States [10]. Similarly, as of 2022, the production, transport, and processing of oil and gas produced 5.1 billion tons of CO_2 equivalent, accounting for a little less than 15% of the worldwide energy sector's greenhouse gas emissions [11].

With that in mind, a new battle against climate change presented itself for environmental reasons and, most importantly, because humans' survival depends on it. Consequently, reducing greenhouse gas emissions became crucial to mitigate these effects and preserve global health. This means making more environmentally friendly decisions about energy use and transportation since they are the two main causes of emissions [12].

Buildings are one of the main contributors to excessive energy consumption and carbon emission [13]. This sector plays a critical role in the energy context and contributes significantly to both overall greenhouse gas emissions and global energy consumption, according to the EIA [14]. Additionally, the residential sector was responsible for 37% of the world's CO_2 emissions and 36% of the global energy consumption in 2020 [14]. A considerable portion of buildings' energy consumption is attributed to their heating and cooling (HVAC) systems, which represent around 40% of the total energy used in buildings [15], making them a key factor in carbon emissions.

As a result, strategies for improving energy efficiency and economic evaluations for various types of existing buildings, including residential and non-residential structures, have been the subject of extensive studies [16,17]. One technique used for reducing building energy consumption and HVAC system optimization is through energy transition [17]. The concept of energy transition involves replacing traditional energy resources with sustainable alternatives, such as solar or wind energy [18,19], with the goal of increasing energy efficiency and reducing the carbon footprint. Among the famous examples of energy transition technologies is the rising concept of smart buildings [20]. This concept consists of using renewable energy sources, specifically solar photovoltaic (PV) systems, to provide cleaner energy to buildings, thus reducing their energy consumption and carbon emissions.

When photovoltaic solar panels are integrated into renovations or new construction, they can capture solar energy and convert it into electricity [21]. This clean and sustainable energy source presents the potential of creating net-zero or even net-positive energy structures [22]. Buildings can significantly reduce their reliance on the conventional electricity grid by utilizing solar energy to power their HVAC systems and other electrical needs, resulting in lower energy costs and reduced greenhouse gas emissions.

Recent works addressed this issue using different methods [23,24]. For instance, in [25], the authors studied the case of a hotel building in the Croatian Adriatic aiming for an nZEB system using an HVAC module. Their work demonstrates that, in association with the HVAC system, a solar photovoltaic (PV) system is crucial to reach nZEB. However, according to [26], the best type of HVAC system to adopt varies depending on the building and its location. For instance, in the case of a building located in a tropical, warm, and humid environment, an air-cooled system with ventilation provides the best results at optimal costs. Likewise, in [27], the authors compared an air-conditioning system coupled with a PV system to a solar cooling system. Their work draws conclusions based on a case study in Jordan, which confirms that when electricity tariffs are based on the total demand, instead of the peak demand, absorption chillers barely offer any financial benefits [27]. Moreover, it proves that a PV system combined with air-conditioning requires less maintenance than a solar cooling system, thus making it more feasible and practical.

In the same perspective, additional measures can be taken to facilitate energy transition using smart buildings [28], and that can be achieved by incorporating a range of interconnected technologies, sensors, and systems that enable the automated control and management of building functions. This not only ensures the efficient use of resources, such as electricity and water, but also enhances the quality of life and workplace experience for occupants by providing a responsive and adaptive environment [29].

Smart buildings make significant contributions to global sustainability and urban development goals by addressing issues such as energy consumption, environmental conservation, and well-being [29]. They can continuously learn and adapt to the requirements of their residents and the surrounding environment thanks to the combination of the Internet of Things (IoT), artificial intelligence (AI), and data analytics. This technological integration not only optimizes resource utilization but also aligns with the principles of sustainability, thus contributing to the achievement of Sustainable Development Goals (SDGs) [30], particularly in fostering sustainable cities and communities [31] (Goal 11) and ensuring access to affordable, reliable, sustainable, and modern energy for all (Goal 7) [32].

Correspondingly, the Internet of Things (IoT) is an essential component of smart buildings, allowing for the integration and coordination of numerous technologies and systems to reduce energy usage, increase occupant comfort, and enhance overall building performance [33–35].

Consequently, it is imperative to minimize energy consumption and carbon emissions in buildings while addressing energy and environmental challenges. To this end, this review article aims to serve as a comprehensive reference guide for the approaches to building control to help shed light on the challenges facing control methods in the building sector, the strategies deployed, and the areas of improvement.

This paper reviews the recent developments in control strategies for researchers, users, and interested parties within the building sector, including those concerned with HVAC systems, whose aim is to ensure thermal comfort and reduce power consumption in buildings. This document also looks at different building modeling approaches and software, highlighting their importance in the development of energy-efficient strategies. In addition, it focuses on classifying control strategies in the building sector, covering traditional control methods, advanced control techniques, and intelligent controls such as artificial neural networks (ANNs) and long-term memory controls (LSTMs). Finally, this article explores the hardware implementation of smart building solutions and their integration with the Internet of Things (IoT), offering a holistic perspective on modern advances in building technology.

This paper is structured as follows Figure 1: Section 2 is a description of our methodology for constructing this review. Section 3 provides a detailed analysis of our review regarding the building modeling approaches as well as the categorization of control strategies in buildings. Section 4 is a discussion of our findings. Section 5 provides a detailed description of the implementation of smart building technologies. Finally, we summarize our afterthoughts in the conclusion.

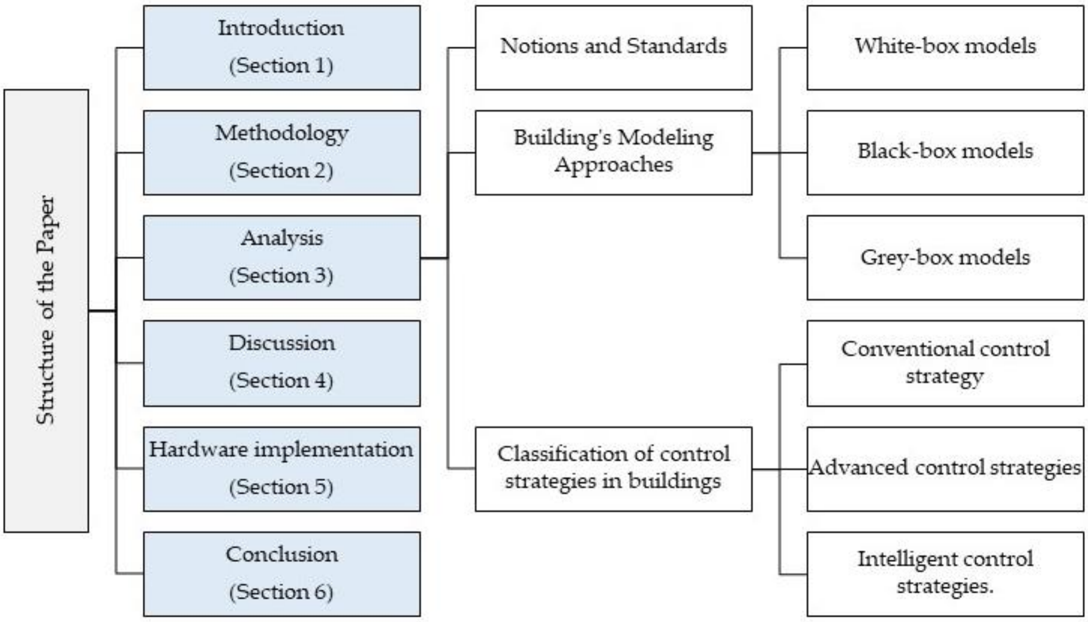

Figure 1. Structure of the paper.

2. Methodology

This section presents the sources, requirements, and methods that were utilized to choose and collect the papers in the literature. This study's objective is to analyze several sustainable alternatives in the context of standards, modeling, control strategies, and methods that will reduce building energy consumption and maintain thermal comfort.

To ensure the completeness of our research, we have formulated key questions to structure the literature review, provide relevant findings from the selected literature, and support the discussion. The questions include the following:

- What are the national and international regulations and standards governing the energetic envelop and thermal comfort in buildings?
- What building modeling methods are available in the literature?
- What control methods are currently deployed in buildings to minimize energy consumption and ensure thermal comfort?
- What is a smart building?
- How are these control methods evaluated in the literature, and how does the term smart building contribute to this evaluation process?

A total of 205 publications were collected from several databases, such as Google Scholar, Scopus, and Web of Science, to conducts a comprehensive analysis and expand our understanding of the topic.

In order to obtain a more comprehensive understanding of the matter, we initiated our research by employing the keywords "Building", "standards", "Building Modeling techniques", and "Building control strategies" to discover innovative approaches for this study.

Using the identical keyword combination, a search was conducted in both Google Scholar and Scopus, resulting in 300 findings. The combination of the keywords yielded 205 articles, with 23 duplicates being removed. By conducting an initial analysis, relevant terms or words were identified in the titles or abstracts, leading to the discovery of 182 articles. The second filter examined the entire contents of the publications to identify a pertinent analysis related to any of the research inquiries, resulting in a total of 167 articles, as depicted in Figure 2.

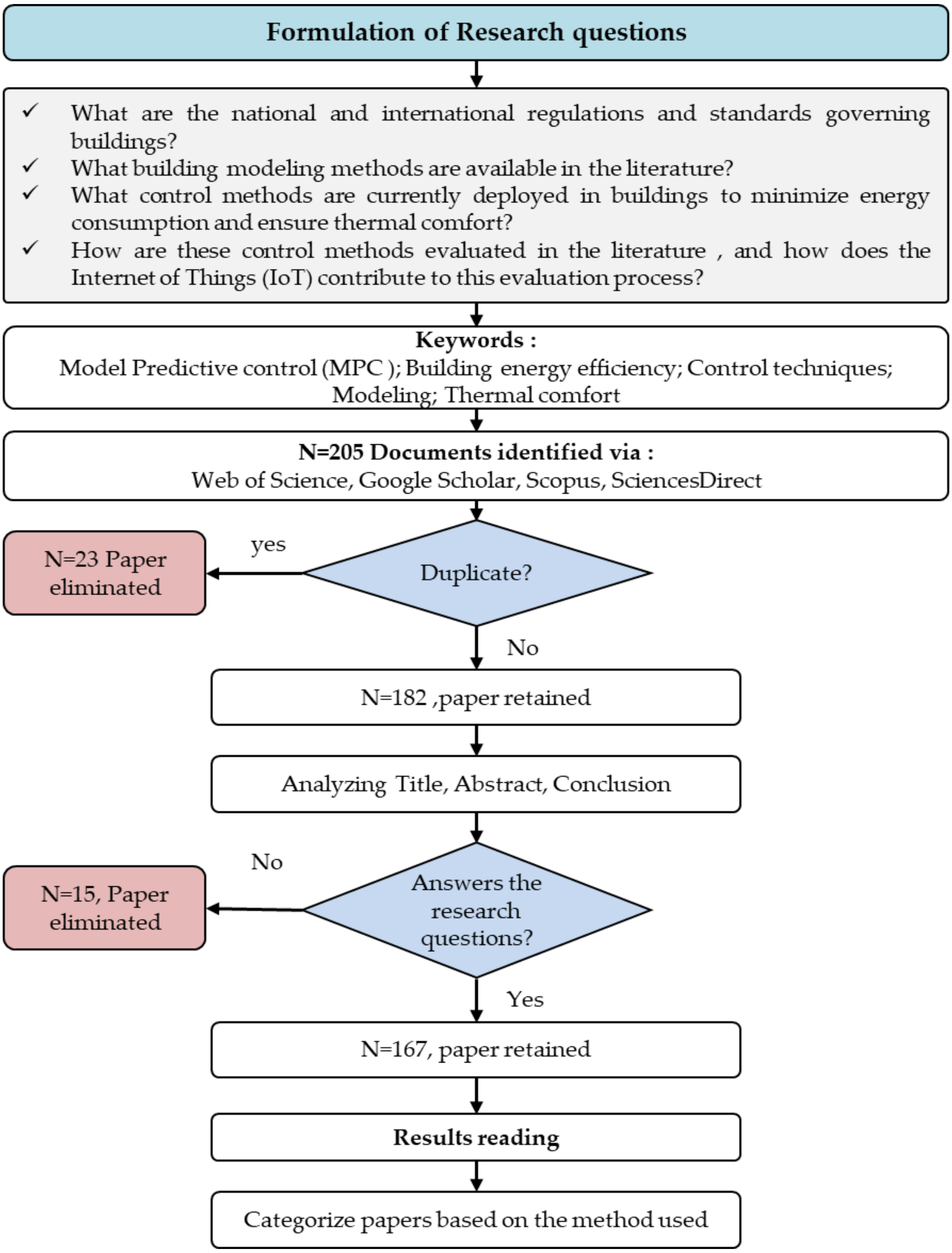

Figure 2. Research process.

The research questions were systematically investigated, followed by a thorough examination of the identified references.

Articles were organized in two categories. The first category regroups review articles which were used as a source of inspiration for the previous state of the art regarding the aforementioned questions. The second category covers the articles that tackle a use case related to our subject. To establish relevance to the study issues, the selected articles were extensively analyzed, including the findings and conclusions. The iterative process involved formulating research inquiries and undertaking a comprehensive evaluation of the existing literature to ensure the pertinence and accuracy of the study.

3. Analysis

3.1. Notions and Standards

Significant energy consumption is associated with the building sector, which is at the center of environmental and energy concerns both internationally and in Morocco.

Since the industrial revolution, the availability of affordable energy has become the backbone of modern societies, leading to a global dependence on fossil fuels. The data show that 66% of the world's primary energy is derived from fossil fuels, with oil predominating at 40% [36]. By 2022, global coal consumption had increased to 6.3% of the global primary energy consumption level [37]. Despite the current environmental impacts and energy crises, renewable energy sources account for only 24% of electricity production worldwide, with the building sector consuming the most electricity at 48% [37]. In Morocco, the building sector is a major energy consumer and embodies the country's energy and environmental challenges, comprising 52% of the final electrical energy consumption [38]. The country, which is heavily dependent on fossil fuels, saw a significant 32% increase in its energy consumption between 2007 and 2017, intensifying the challenges linked to energy security and CO_2 emissions. Faced with this reality, bold energy and environmental strategies have been implemented to increase the proportion of renewable energy in electricity production to 52% by 2030 [38]. These initiatives also aim to counter the accelerated growth in emissions in various sectors and to reduce the ecological footprint of the building sector, which is set to play a major role in achieving sustainable development objectives, both nationally and internationally.

However, the building sector is characterized by the presence of several standards and regulations at both the international and national levels:

- ISO50001

International standards, such as ISO50001, which was initially published on 15 June 2011 by the International Organization for Standardization (ISO), have the main objective of providing clear guidelines for the development of an energy management system focused on energy performance, enabling energy savings and cost minimization. According to the International Energy Agency (IEA), the application of this standard could influence up to 60% of the global energy demand [39].

- ISO7730

ISO7730 [40], developed by ISO/TC159, concerns the ergonomics of the physical environment, specializing in thermal comfort in a variety of environments. It introduces methods for predicting thermal sensation and discomfort using the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD), which assess the level of comfort or discomfort experienced by a group of people in each thermal environment using a 7-level scale, shown in Figure 3. The PMV is based on the thermal balance of the human body, taking into account various environmental and personal factors [41]. The standard mainly applies to environmental and architectural design with the aim of maximizing thermal comfort and minimizing discomfort and dissatisfaction.

- ASHRAE90.1

ASHRAE90.1, with the exception of low-rise housing, is a standard established by ANSI and published by ASHRAE in collaboration with the IES that sets minimum requirements for the design of energy-efficient buildings. The first version was published in 1975 and has been regularly amended since 1999. In 2001, it was renamed ASHRAE 90.1 in response to changes in technology and fluctuating energy costs. There are two compliance options: prescriptive compliance, which imposes minimum standards for each element, and performance-based compliance, which requires the building design to exceed the ASHRAE 90.1 reference model in terms of energy consumption, calculated in US dollars [42].

- NF EN 15232

The European NF EN 15232 standard sets out methods for assessing the impact of building automation and management (BAM) systems on the energy performance of buildings in seven areas, including heating and lighting. It provides calculation methods for assessing the effectiveness of control management and guidelines for integrating BMS functions into existing standards. As a result, this standard facilitates the harmonization of standards and operational activities relating to building control systems [43].

- NF EN 16247

The standard and reference methods for energy audits in key energy-consuming sectors, such as the building, industry, and transport sectors, are defined in the European standards package, NF EN 16247 [44]. It supports the regulations in force in France, which require large companies to carry out mandatory energy audits. The NF EN 16247-1 standard, published in 2012, defines an energy audit as a methodical analysis of energy use and consumption and sets out the general requirements for carrying it out [44]. All of the stages of the energy audit are covered by the NF EN 16247-2 standard, which was published in 2014.

- Japan

In Japan, since 1979, energy regulations for buildings have varied depending on the building type, with standards being set to ensure compliance and increase energy consumption in residential and domestic systems [45].

- India

As the world's third-largest energy consumer, India has three different building codes: the National Building Code of India (NBC), the Energy Construction Building Code (ECBC), and the Environmental Impact Assessment and Approval (EIA). From 1974 to 2020, several thermal regulations (TRs) have been put in place in France with the aim of reducing the energy consumption of buildings by encouraging the construction of positive energy buildings and passive houses while increasing energy production and reducing energy waste [46].

- Canada

In Canada, the National Energy Code for Buildings (NECB) was adopted to promote consistency between provincial and territorial building codes, since the latter have the authority to legislate on the construction of buildings within their territory [47].

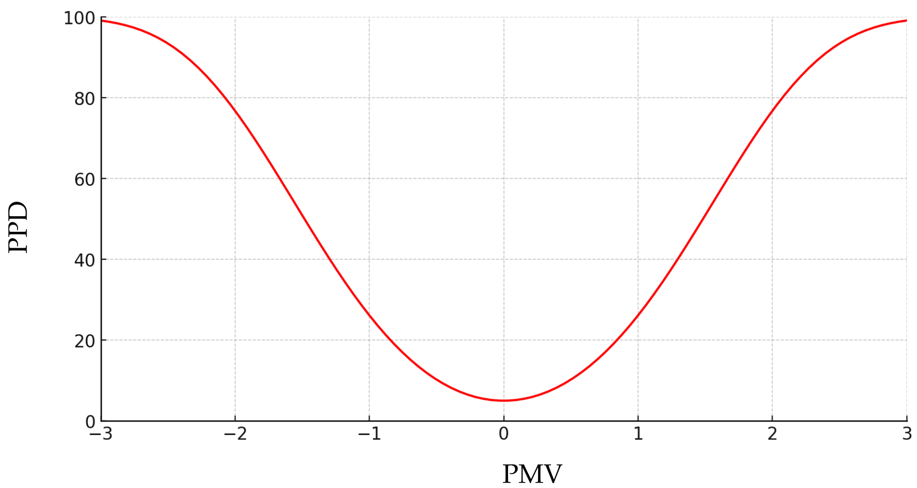

Figure 3. Correspondence between the PMV and PPD factors [48].

$$\mathrm{PMV} = 0.303\mathrm{e}^{(-0.036\mathrm{M})} + 0.028. \quad (1)$$

M shows energy metabolism in $\mathrm{W/m^2}$ [48].

- Spain

The construction and maintenance of buildings in Spain are governed by the standards of the Energy Performance of Buildings Directive (EPBD) [49].

- Algeria

In 2000, thermal regulations were introduced in Algeria with the aim of reducing the heating consumption of buildings [50]. These regulations use two calculation techniques to assess heating and cooling costs. The authors of [51] developed these calculation techniques.

- Italy

Since the 1970s, laws on energy conservation in buildings in Italy have been in force, dealing with various issues such as minimum energy consumption, renewable energy installations, and the classification of energy consumption [52].

- Tunisia

In 2008, thermal regulations were introduced in Tunisia [53] for buildings that use water sources. In 2009, the objective for buildings intended for residential use was to improve thermal performance using prescribed and formative methods [54]. Each country modifies its regulations to meet its own needs and climatic conditions.

- Morocco

In Morocco, the introduction of thermal regulations was promulgated by decree No. 2-13-874, which was implemented on 15 October 2014 [55]. The decree endorses global requirements for construction, with a particular focus on improving the energy efficiency of buildings. The Moroccan Agency for Energy Efficiency produced "Thermal Regulations for Construction in Morocco (RTCM)" to optimize the energy performance of new buildings [55].

With the aim of promoting a sustainable future and preserving the environment, the construction industry has effectively integrated green building practices. With a focus on optimizing energy efficiency and designing environmentally friendly buildings, numerous labels, certifications, and standards have been introduced around the world to support this commitment, each adopting its own approach, methodology, and set of standards. Figure 4 presents the chronology of the creation of some international labels.

When it comes to assessing the environmental quality and energy performance of eco-homes [56] and buildings for energy efficiency and the life cycle of a building, we use the LEED certification. Minergie focuses on building comfort and energy efficiency by emphasizing eco-friendly materials and energy conservation [57]. Several other labels and certifications are presented in [58].

- BREEAM

The Building Research Establishment Environmental Assessment Method label aims to define standards of good practice for the sustainable design, operation, and construction of buildings; its main aim is to reduce the environmental impact of buildings throughout their lifecycles by promoting environmentally friendly methods and optimizing energy efficiency. In addition, it aims to guide and inspire builders and designers to adopt sustainable strategies and apply environmentally safe strategies and sustainable solutions in their construction plans, while providing a certification that highlights initiatives in favor of sustainability and energy excellence [59].

- HQE

The HQE label is a French environmental protection concept that focuses on the overall management of the environment across the entire life cycle of a building. It requires 14 objectives to be respected and encourages low-impact technological applications and alternative energy sources. Unlike other French labels, the HQE label is a registered brand. To qualify, buildings must satisfy 14 objectives, which guarantee energy efficiency and a balance between interior comfort and environmental impact [60].

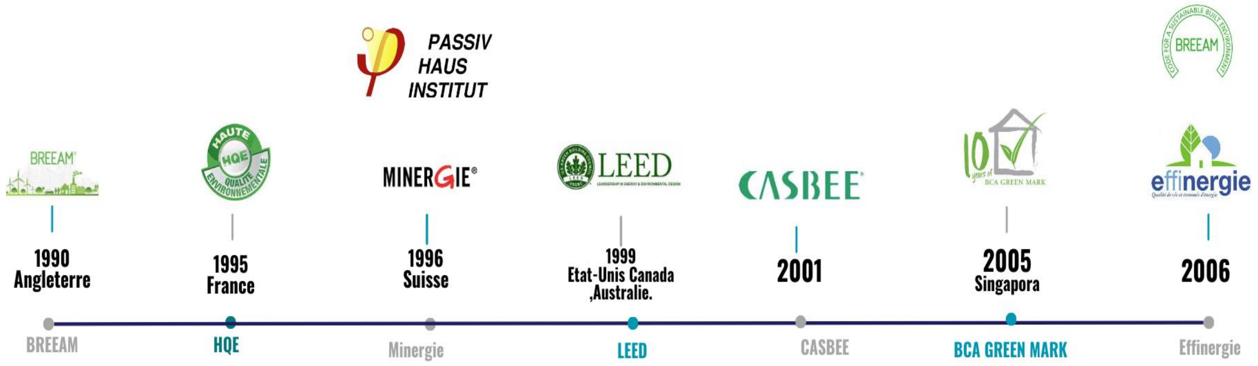

Figure 4. A chronology of the creation of some international labels [61].

3.2. Building Modeling Approaches

Various modeling techniques can be distinguished for analyzing the thermal dynamics of a building, such as the white-box, black-box, and gray-box approaches [62].

White-box modeling is the detailed modeling of multizone structures using physical concepts of energy, momentum transfer, and mass. This includes heat transfer modeling for all building components, such as the roofs, floors, windows, walls, doors, and furniture. Figure 5 presents three subcategories of white-box modeling: computational fluid dynamics (CFD), the zonal method, and the W-multizone approach [62]. The W-multizone modeling approach assumes uniform thermal characteristics for each layer and combines the temperatures of each layer into a single state [63]. However, it may not provide accurate results for large-volume zones. On the other hand, both the zonal and W-multizone approaches are commonly employed in popular commercial software, such as TRNSYS, EnergyPlus, or Modelica-based open-source libraries, to simulate the thermal dynamics or energy use of multizone buildings. The modeling techniques, benefit limitations, and applications of frequently used software, such as EnergyPlus, TRNSYS, Dymola, and other tools, are discussed in [64].

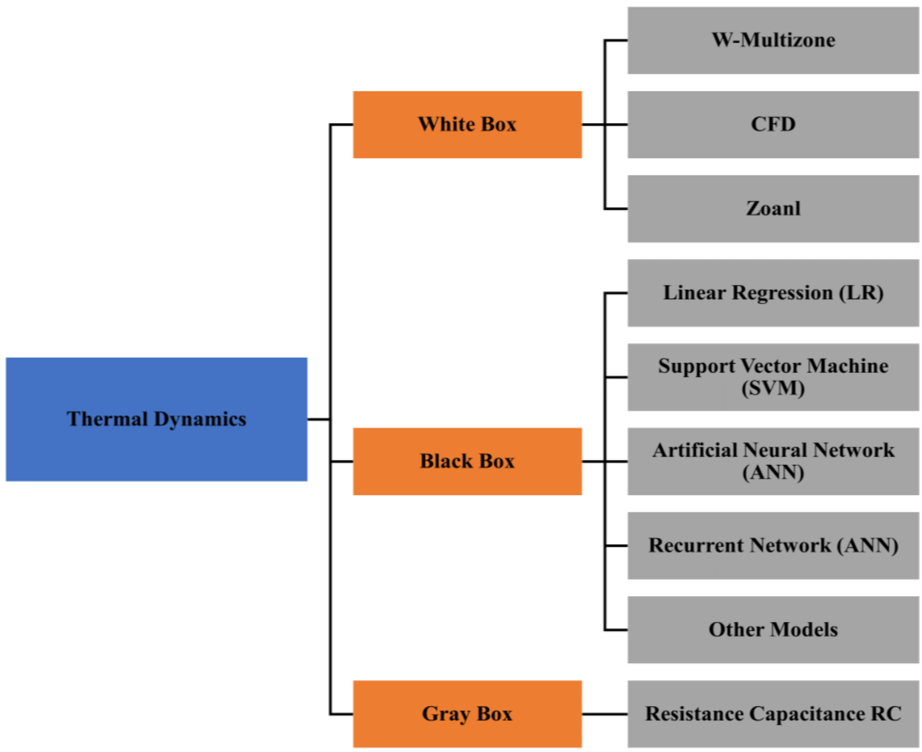

Figure 5. Building thermal dynamics [64].

Figure 6 illustrates the many software programs used for creating physical energy modeling. The programs utilizes heat and mass balance equations, considering heat transfer through conduction, convection, and radiation between the building envelope and its surroundings. The principal goal of this program is to estimate and analyze building energy consumption and thermal behavior [64].

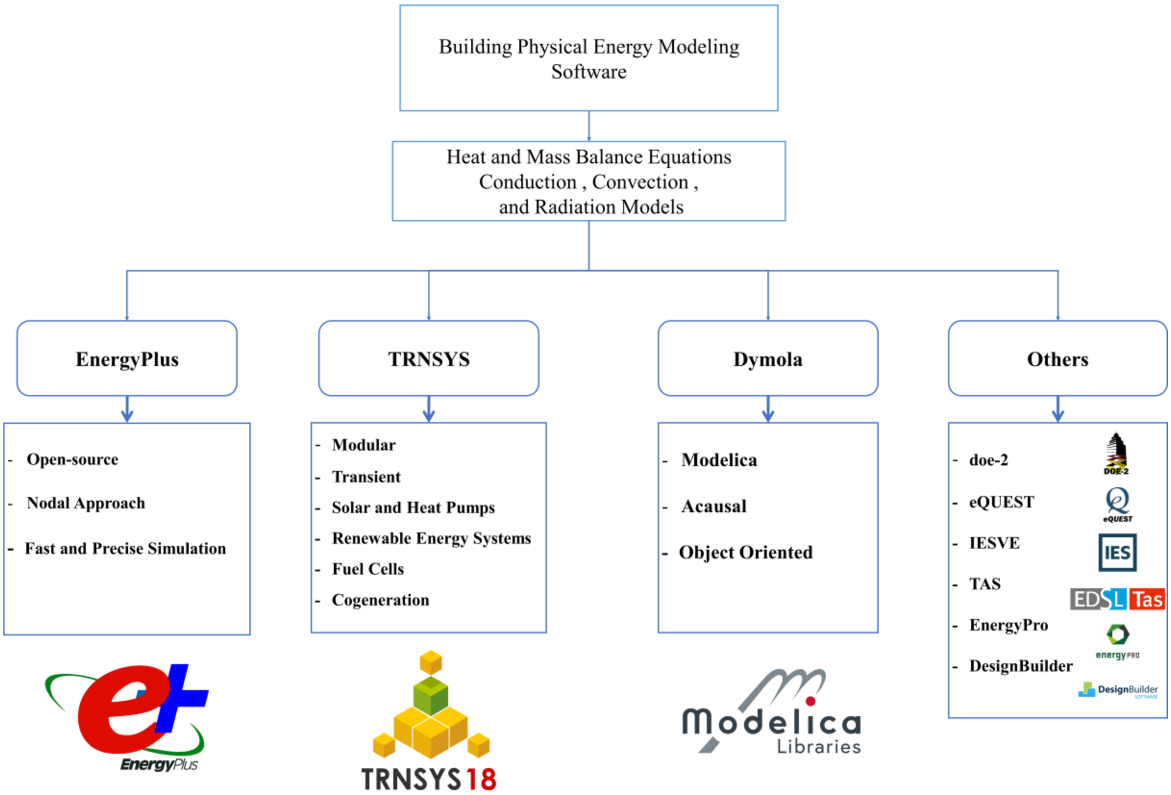

Figure 6. The different software used for building physical energy modeling [64].

An overview of building performance simulation tools (BPS) is presented in [65], with the researchers particularly focusing on HVAC (heating, ventilation, and air-conditioning) systems. One study [66] concentrates on the multiobjective optimization of building design using TNRSYS simulation, genetic algorithms, and artificial neural networks. The main purpose of this research is to develop optimal building designs that achieve a balance between different conflicting objectives, such as thermal comfort, energy efficiency, and cost-effectiveness. The researchers aim to systematically explore the vast design space and identify solutions that effectively meet these diverse requirements. To accomplish this, they employ a combination of TNRSYS simulation, genetic algorithms, and ANNs.

The white-box building modeling software is a methodology that employs software to accurately replicate the energy systems and control mechanisms of a physical building.

EnergyPlus is a popular open-source energy modeling program for buildings that has been in development since 1997 and was launched in 2001 [67]. It estimates a building's thermal performance over broad time scales using a nodal method with conduction transfer functions and finite-difference techniques. EnergyPlus is well known for its quick simulation speed and accurate assessment of energy consumption, making it useful for monitoring energy usage in diverse buildings and systems.

Despite its capabilities, HVAC system modeling in EnergyPlus may be difficult and time-consuming [68]. EMS programs have been built by researchers to improve HVAC system simulations, but historical operational data from real buildings are critical to improve forecast stability. Overall, EnergyPlus is a great tool for energy analysis in buildings, while modeling HVAC systems requires extra care to obtain correct findings [69].

On the other hand, transient system simulation (TRNSYS), developed by the Solar Energy Laboratory at the University of Wisconsin-Madison, is a flexible and modular tool used for various applications such as solar systems, buildings, HVAC systems, renewable energy systems, fuel cells, and cogeneration [70]. It features a graphical user interface and allows users to develop personalized components or types. TRNSYS is commonly utilized to model building energy systems, particularly for solar energy systems and heat pumps. Researchers have employed TRNSYS to investigate geothermal heat pump systems and grid-connected photovoltaic (PV) systems, achieving accurate long-term energy performance predictions [70]. A study that compared EnergyPlus with a multi-zone dynamic simulation application (IDA ICE) found that TRNSYS was the most accurate at predicting what would happen during a warm period when a phase change material (PCM) was not present, while IDA ICE was the most accurate during the cooling period. TRNSYS not only forecasts energy consumption, but also facilitates energy system design for optimization [71].

The black box model, also known as a purely data-driven model, is used to capture the correlation between a building's energy consumption and operational data. It requires on-site measurements over a specific time period to train the model to predict how the building will operate under various conditions. These models are commonly applied in research to determine building control strategies aimed at reducing energy consumption and costs. Reference [71] explores the utilization of data-driven models employing machine learning algorithms known as black-box models. These models have a vital function in the development of energy systems, as they are used for both energy prediction and optimization.

The use of data-driven approaches in the image-based BIM construction process is covered in [72], which primarily relies on the information or data collected about a building to detect objects. The article also discusses the opportunities and problems that come with using image-based BIM construction processes, such as the need for low-cost data collection procedures, efficient data management, and so on. In [73], whole-building energy modeling and prediction is presented. These models may be utilized for structures without precise physical characteristics. By using mathematical techniques, these models employ historical data to identify links between input and output factors.

Gray-box models are hybrid models that replicate the behaviors of building energy systems using reduced physical descriptions. The use of simpler physical models decreases the need to train data sets and reduces the computation time. Model coefficients are discovered using statistics or parameter identification methods based on operating data. In prior work, a novel three-step approach for building and training gray models was created [74]. The researchers in [75] evaluated the robustness of black-box and gray-box models for predicting thermal building behavior in response to changing weather conditions. It concentrated on model predictive control (MPC) for space heating, as well as its dependency on accurate predictive models. Gray-box models outperformed black-box models in terms of prediction ability and robustness to weather data variations.

3.3. Classification of Control Strategies in Buildings

The control of HVAC (heating, ventilation, and air-conditioning) systems is fundamental for ensuring thermal comfort in buildings without increasing energy consumption. For this reason, several methods and strategies for technical control are available and can be classified into different classes [76,77].

Starting with standard or classical control strategies, the two subcategories of this technique are PID control (process control) and on/off control (sequencing control).

These types of techniques are frequently employed to regulate HVAC components that utilize the signal from simple sensors, which include humidistats, thermostats, or pressure switches [78]. In fact, in the context of control systems, there is a growing understanding that standard or traditional control approaches may not always be effective to manage the complexity and uncertainties found in many real-world applications. This has led to the development of soft control or intelligent control approaches, which use sophisticated algorithms and computer intelligence to provide more flexible and adaptable control strategies.

Additionally, hybrid control [79] has become a powerful tool in the field of control systems, combining the advantages of flexible control techniques, such as fuzzy logic and artificial neural networks, with conventional or sophisticated control approaches.

3.3.1. Conventional Control Strategy

PID and on/off control are two subgroups of the classical control approach, as shown in Figure 7. They are the most frequently employed controllers in HVAC systems in both commercial and residential buildings due to their simple structures and economical initial costs [80]. However, one of the main weaknesses of conventional control systems is their lack of connection with the external environment (grid/meteo/city), which prevents the adoption of high-efficiency control [80].

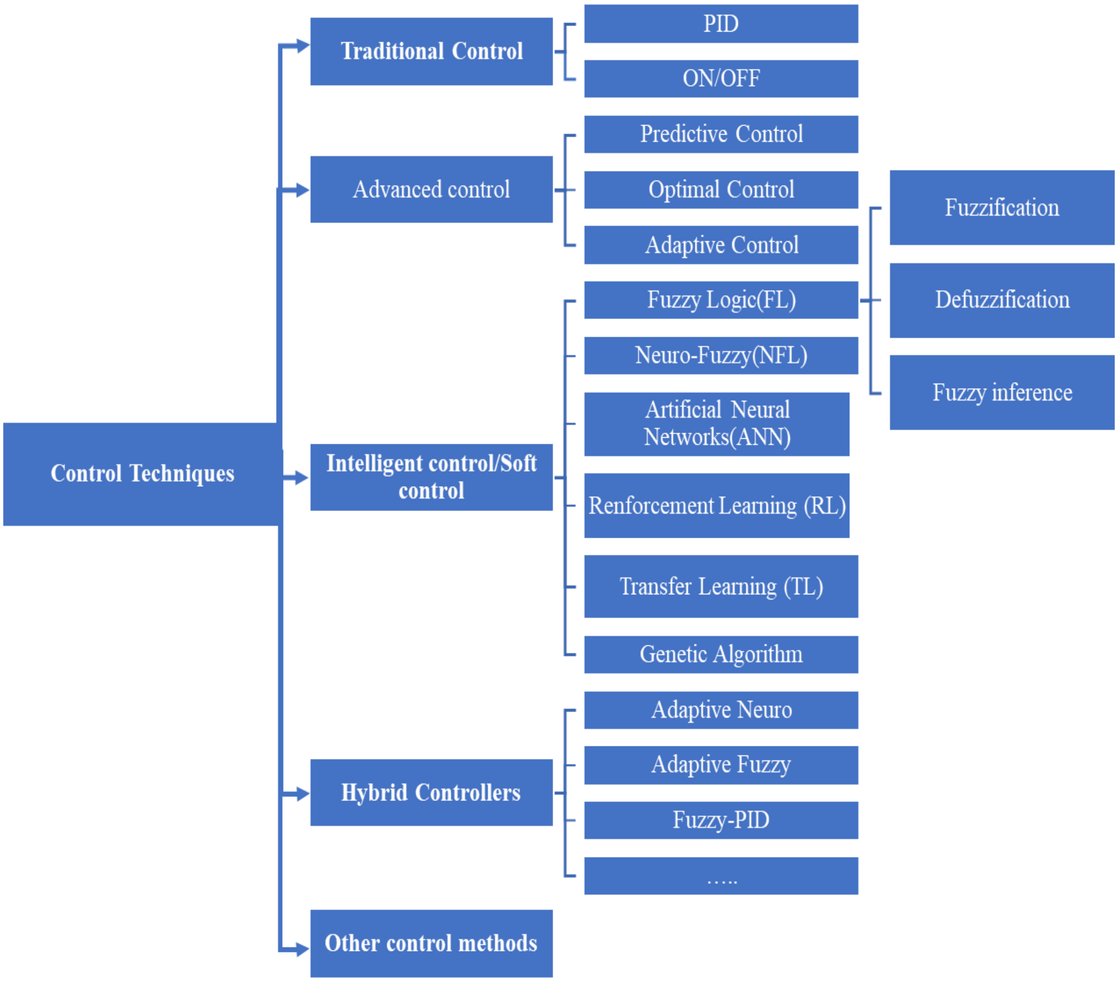

Figure 7. Control strategies [76].

Proportional–integral–derivative (PID) control is commonly used in many HVAC systems; it is a closed-loop control system that continuously measures the process variable and adjusts the control signal to maintain it at a desired setpoint [81].

The proportional action provides an immediate response to the present error and helps reduce the steady-state error. The integral term considers the accumulated errors over time and helps eliminate the steady-state error. The derivative term predicts the future error based on the rate of change of the process variable and helps improve the system response to sudden changes in the process [81].

The combination of these three actions (P, I, and D) helps to improve the stability and response of the control system [82]. This is expressed in Equation (2):

$$u(t) = K_p e(t) + K_i \int_0^t e(t) d_\tau + k_d \frac{de(t)}{dt} \quad (2)$$

In Equation (2), u(t) denotes the control variable, e(t) represents the value of the error between the deserted setpoint and measured feedback, and K_p, K_i, and K_d indicate the coefficients for the P, I, and D terms.

For some applications, it might be preferable to apply one or two of the three actions and put the other two at zero. Figure 8 presents the action of a PID controller. The two most commonly used control algorithms are P control and PI control. A building's thermal process dynamics is a slow response procedure. As a result, P control can potentially be used to regulate a building's temperature with a reasonably small offset and good stability. It also works well for controlling a building's humidity [83,84].

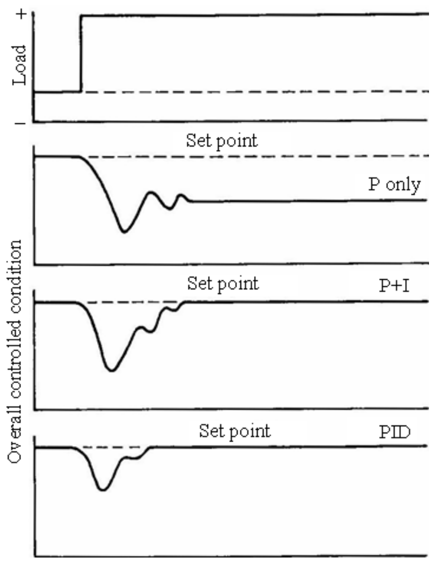

Figure 8. PID controller [83].

The main advantages of PID control are that it does not require a mathematical model of the system, it is simple to implement, and it allows for the powerful and flexible control of a linear system [84].

However, PID controllers have some drawbacks, such as their inability to handle cross-coupling (multi-zone) nature and constraints in HVAC systems, which are difficult to tune and may be sensitive to system changes [85]. The main advantages and disadvantages are presented in Table 1.

An on/off control system is a feedback control technique that has been used for many years in various applications, including in buildings, for energy conservation and occupant thermal comfort. It is a binary control system that operates on a simple and fast principle, where the output device is switched on or off based on the measured input signal. This technique is widely used in domestic and commercial buildings through devices such as thermostats, humidistats, and pressure switches. Overall, an on/off control system is a straightforward and inexpensive method for controlling various systems and processes. Figure 9 presents the action of an on/off controller.

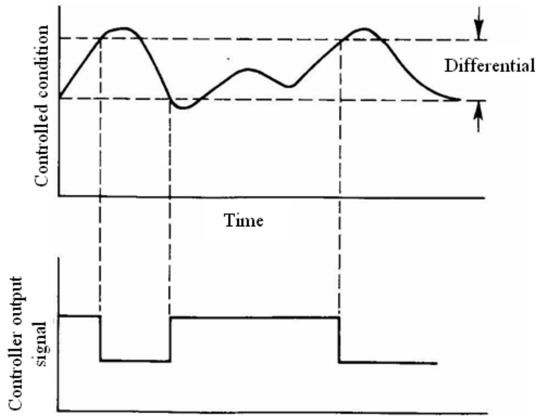

Figure 9. Action of an on/off controller [83].

Oluwasegun and Kayode discuss the challenges associated with turning the proportional–integral–derivative (PID) control law into a closed-loop control in many dynamical systems. They conclude that PID tuning is a non-convex optimization problem, which makes it difficult to achieve accurate and stable control. The authors of [85] review different methods for PID turning and propose a solution to minimize the complexity and cost associated with turning the three main parameters of the PID control law. The article argues that solving this problem can save money and significantly improve PID control design [85].

Fazelpour and Asnaashri highlight the creation of an Earth–Air Heat Exchanger (EAHE) to increase the efficiency and economic competitiveness of household HVAC systems. The system employs a natural pre-heat/cool coil that is controlled by a PID controller built into the HVAC system, obviating the requirement for additional control equipment. Finally, the authors of the article find that, based on the time of year and temperature of the downstream zone, the PID setting of the DDC may be adjusted for control process optimization. And to reduce energy usage during the changeover season, the system may exclusively use outside air [86].

Shein and Tan focus on the use of a PID controller and a hybrid controller to regulate two actuators (air conditioner and a window) in a cyber-physical home system for temperature management. The authors' goal is to maintain the ideal room temperature while using as few resources as possible. They conclude that traditional building controllers are inefficient and inflexible enough to adjust to changes. The article aims to investigate the effectiveness of the controllers in maintaining a desired room temperature with only two actuators. The suggested cyber-physical-system-based HTC system is studied and validated using MATLAB/SIMULINK simulation [87].

Another article addresses the implementation of a proportional control system for the HVAC system of a residential building. It concludes that the typical two-position (on/off) management method utilized in residential buildings lacks energy efficiency and thermal comfort. However, energy consumption does not show much difference between the two control schemes. Finally, the authors affirm that proportional control has advantages over on/off control relative to equipment life due to a smoother control signal [88].

Finally, classical controllers perform some functions that are acceptable, but they are very expensive due to their poor performance and high maintenance requirements. As a result, advanced and intelligent control techniques, such as model predictive control (MPC) and fuzzy control, are becoming more popular in preference compared to less energy-intensive systems that provide thermal comfort.

Table 1. Advantages and disadvantages of classical control strategies.

Control System	Advantages	Disadvantages	Ref.
On/off control	Simple and easy to implement, low cost	Poor temperature control, can cause wear and tear on HVAC equipment	[76]
	Energy-efficient, reduces carbon emissions	Poor temperature control, limited application in areas without favorable climatic conditions	[89]
	Simple and adaptable control methods	Limited accuracy and performance compared to more advanced control techniques	[83]
	Cost-effective, energy-efficient, adaptable to various HVAC systems	Limited accuracy and performance compared to more advanced control techniques	[76]
	Improved energy efficiency, better temperature control	Can be complex and expensive to implement	[90]
PID control	Improved energy efficiency, better temperature control	Complex system modeling required data	[88]
	Improved temperature control, adaptable to various HVAC systems	Require expert knowledge and time-consuming turning	[76,85]
	Improved temperature control, adaptable to various HVAC systems	-	[81]
	Fast response improved performance, adaptable to nonlinear objects	May require complex implementation and parameter turning	[91]
	Simple and inexpensive	Poor control, accuracy, and stability	[77]

3.3.2. Advanced Control Strategies

This section focuses on sophisticated control systems with a particular emphasis on tree-based methods. We will thoroughly examine model predictive control, including its many forms and important aspects for comparison. We will also cover optimum and adaptive methods of control in a clear way.

Model Predictive Control (MPC)

Model predictive control (MPC) minimizes a defined action over a fixed time horizon to determine control actions. It entails predicting and optimizing future system behavior using a mathematical model of the system, current state measurements, and disturbance predictions. Moreover, it is a sophisticated type of process control that is effective at satisfying constraints and has been widely implemented in a variety of fields, including the building and construction industries. It has a number of technical specialties and features that make it a popular choice for control strategies in building systems, such as control precision, stability, and interference immunity, which result in energy savings and improved control performance [92,93]. MPC is a restricted optimum control approach that determines the best control inputs by minimizing a specified objective function over a finite prediction horizon. The mathematical model of the system, along with the present state data and weather forecast, are utilized to anticipate and optimize a building's future behavior [93]. The general MPC formulation for a building is presented in [92], as the following optimal control problem in discrete time:

$$\min_{U_0,\ldots..,U_{N-1}} L_n(x_N) + \sum_{K=0}^{N-1} L_K(x_k, y_k, r_k, u_k, s_k) \tag{3}$$

The MPC scheme comprises several key components, as presented in Figure 10: a system prediction model, an objective function, constraints, a disturbance model, a control horizon, and an optimization method. They might all have an impact on MPC's performance. Additionally, each component can be modified or adjusted to suit various possibilities, resulting in a variety of algorithms with distinct properties [93,94].

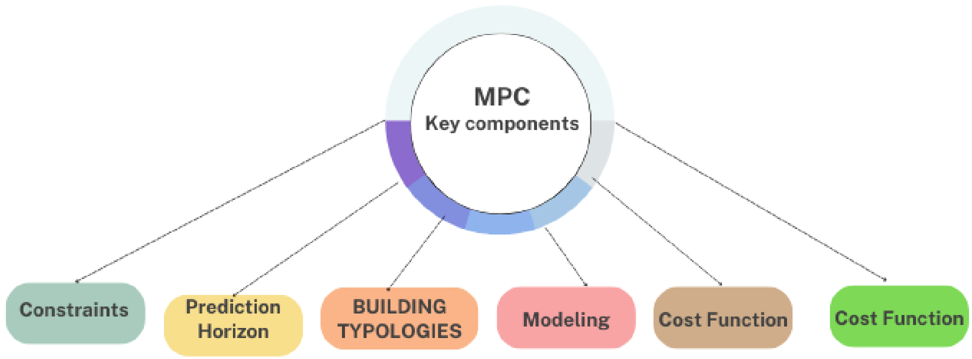

Figure 10. Factors affecting MPC performance [94].

- Types of MPC

Model predictive control (MPC) is a strategy for controlling a system by minimizing a given objective function over a finite prediction horizon. It involves using a mathematical model of the system, along with current state measurements and disturbance predictions, to predict and optimize future system behavior.

The three key steps involved in MPC are developing and identifying moles, predicting disturbances, and solving optimization problems by incorporating predictive information into the model. MPC has demonstrated its potential to save energy and improve control performance in numerous applications [94]. Figure 11 illustrates the many forms of MPC, while Table 2 presents a concise overview of the benefits, drawbacks, and intended applications of each type.

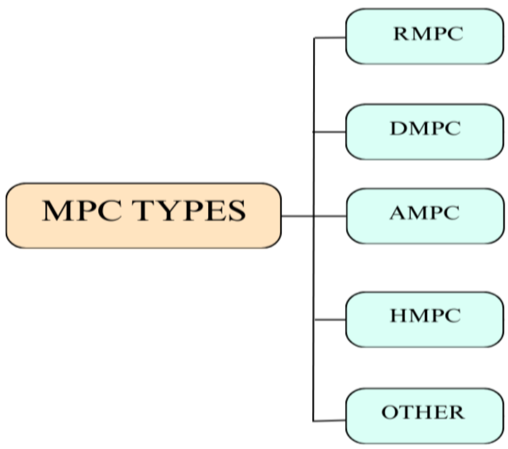

Figure 11. MPC types [92].

Table 2. Types of MPC control systems [93].

Method	Advantages	Objectives	Applications	Limitations	Ref.
RMPC (Robust MPC)	Robustness to uncertainties and disturbances	In the presence of uncertainty, it maintains desirable setpoints and reacts to disturbances	Any HVAC system	Computation complexity, turning complexity, sensitivity to modeling errors	[95,96]
SMPC (Stochastic MPC)	Consideration of probabilistic nature of uncertainties	Maintains desired setpoints and responds to disturbances while considering the most likely disturbances that may be encountered in practice	HVAC systems with uncertain and varying disturbances	Computational complexity, potential for instability or oscillations, limited applicability to certain types of systems	[97,98]

Table 2. *Cont.*

Method	Advantages	Objectives	Applications	Limitations	Ref.
DMPC (Distributed MPC)	Splits large-scale applications into smaller subproblems	Reduces computational burden and increases efficiency	Suitable for multizone buildings and water distribution systems	May lead to increased communication and implementation complexity	[99,100]
AMPC (Adaptive MPC)	Adaptability to changing system dynamics Handles model uncertainties and updates models based on data measurements	Responds to changes in system dynamics or parameters over time Ensures stability of the system	Suitable for non-linear and transient systems	May not work well with systems with large model uncertainties	[38,39]
HMPC (Hybrid MPC)	Energy savings and improved performance	Combines the benefits of different types of MPC systems to achieve better performance and energy efficiency	Additional complexity and computational requirements, potential for communication delays or failures	HVAC systems with multiple operation modes or components	[101]

1. Robust model predictive control (RMPC)

Due to divergent models or change factors, accurate modeling in buildings and HVAC systems is not achievable. Exogenous disruption elements include the zone temperature, occupancy rate, external temperature, cooling loads, sun irradiation, and more. As a result, uncertainties provide a challenge in the design of heating and cooling systems [93]. Uncertainties are challenging for an MPC control system because they affect its accuracy and ability to be implemented correctly in real systems. Building a robust model predictive control (RMPC) system may be a solution to these issues.

An RMPC system is an improved version of a nominal MPC system that ensures all possible uncertainty sequences satisfy the state control constraints; in the constraint problem for RMPC formulation, uncertainties are assumed to be bounded [93].

This paper presents a robust model predictive control strategy for improving the supply air temperature control of air-handling units. It uses a first-order plus time-delay model with uncertain time-delay and system gain, and an offline LMI-based robust model predictive control algorithm to design a robust controller. The proposed strategy is evaluated in a dynamic simulation environment of a variable air volume in an air-conditioning system in various operation conditions, and the robustness analysis of both strategies is also presented [95]. Reference [96] presents a two-level control scheme based on robust model predictive control (RMPC) to offer frequency reserves with a district heating and cooling system. It takes advantage of the thermal inertia of buffer storage tanks and a subset of connected buildings with electric heating and cooling systems. In this paper, the author presents a numerical case study and real-world experiment to validate the control approach, showing that reserves can be offered without compromising comfort in connected buildings.

2. Stochastic model predictive control (SMPC)

Stochastic model predictive control (SMPC) is an alternative to robust control approaches that considers the probabilistic nature of uncertainties and provides additional information about the uncertainties. It is formulated with chance constraints to eliminate the worst-case scenario and take into account the most suitable control algorithm for HVAC systems [102].

3. Distributed model predictive control (DMPC)

The distributed model predictive control strategy (DMPC) is used to divide complex applications into smaller, simpler stets of subproblems that are controlled locally by their inputs and outputs. It is motivated by the need to reduce the computing burden through the right construction of controllers that are capable of performing computations and communicating effectively. DMPC is the most often used control algorithm for creating complicated multi-level zones, rooms, and floors, and it is well suited for decoupling separation [103].

4. Adaptive model predictive control (AMPC)

The adaptive model predictive control (AMPC) method may be a good contender for dealing with such issues. The AMPC is best recognized for addressing model uncertainty and updating models based on data measurements gathered online. This strategy has two key goals: to assure system stability and update time-variant models at each time interval [103].

5. Hybrid model predictive control (HMPC)

The complexity of model dynamics, goals, and constraints in the problem formulation of MPC has increased rapidly. Hybrid model predictive control (HMPC) is a novel intervention paradigm of the MPC scheme controlled through continuous-valued and discrete-valued state components. This class of MPC helps to expand its capabilities for dynamic switching, control variables (i.e., mixed integer or binary integers), and logical states. These control variables lead to the non-linear optimization problem that is solved using optimization algorithms, such as MILP and MIQP. Hybrid MPC systems are categorized into two special classes, i.e., pure discrete systems and a combination of continuous and discrete systems [103].

The necessity of building energy management for the efficiency of the power system is highlighted in this study [104]. The author discusses the current advances in data-driven model predictive control (MPC) and reinforcement learning (RL) algorithms for building energy management systems (BEMSs). Moreover, the study offers recommendations for selecting control strategies depending on known dynamics or modeling challenges. At last, the study suggests using simpler data-driven models with robust control strategies for efficient and reliable building energy management.

Reference [105] explains how model predictive control (MPC) can optimize energy usage and thermal comfort in university buildings, but weather forecast uncertainty poses a challenge to its implementation. To address this issue, the study proposes an error model that utilizes easily measurable data to enhance weather forecast accuracy. Testing the method on a university building in Norway showed that the MPC system with the error model almost achieved the MPC system's full theoretical potential in reducing energy costs and improving thermal comfort. In contrast, the MPC system without the error model performed poorly, resulting in minimal energy cost savings and increased indoor temperature violations. The study concludes that the error model can significantly enhance MPC performance in buildings, even under conditions of low weather forecast error.

The authors of [106] present a research study that explores the use of a hybrid predictive model in a model predictive control (MPC) framework for building energy systems (BESs) that combine batteries and solar photovoltaic (PV) panels. The aim of this study is to maximize the use of renewable energy sources while minimizing the use of non-renewable sources.

The methodology involves developing a model that can predict the behavior of the system over a short period of time (hours) while taking into account long-term trends (days). The model is trained using historical data from the building energy system and weather forecast data. The MPC algorithm is then used to optimize the system's performance by adjusting the setpoints of various components, such as solar panels, battery storage, and heating/cooling systems. The optimization is based on a cost function that takes into account the cost of energy from different sources, as well as the cost of any penalties for exceeding energy consumption limits. The authors of [106] found that the MPC algorithm was able to effectively optimize the system's performance, resulting in a reduction in energy consumption from non-renewable sources and an increase in the use of renewable sources. The results demonstrate the potential of using MPC for renewable energy systems in buildings.

Model predictive control (MPC) is a strategy for controlling a system by minimizing a given objective function over a finite prediction horizon. This process involves the use of a mathematical model of the system, in conjunction with measurements of the current state and effective disturbance management, to meet constraints. This approach has been widely used in many sectors. Table 3 gives an example of the software used to implement it.

Table 3. Model predictive control software.

Article	Advantages	Limitations	Sector	Software
[107]	Increases system efficiency and performance	Difficulty in modeling and accounting for uncertainty	Building energy system	Matlab
[108]	Improves energy efficiency and cost savings	Difficulty in modeling and accounting for weather uncertainty	Building	-
[108]	Improves system performance and energy efficiency	Limited scope of study and generalizability of results	Building	TRNSYS/MATLAB/ Co-simulation testbed
[106]	Improves energy efficiency and cost savings	The long short-term hybrid model is difficult to model and tune	Real office building	-
[109]	Increases cost savings and energy efficiency	Difficulty in modeling and training deep reinforcement learning models	Real office building in Pennsylvania	Intelligent work space
[110]	Increases energy efficiency and cost savings	Difficulty in modeling and training deep learning models	Building	Open Studio EnergyPlus
[111]	Improves control strategies for mixed-mode buildings	Limited to mixed-mode buildings	Building with mixed-mode cooling	Matlab EnergyPlus

Optimal Control

In order to minimize a certain cost function and maintain the indoor environment with high energy efficiency, the optimal control algorithm is used to solve an optimization issue. In this method, control signals are derived to meet certain physical restrictions while optimizing a selected performance criterion [112]. In [113], the authors focused on reducing energy consumption in an office building by presenting an optimal control method for HVAC systems. The system employs two control algorithms that consider the interior thermal conditions, specifically the temperature and humidity, as well as the predicted mean vote (PMV). The control algorithms were evaluated using office equipment, and a survey was used to evaluate the connection between changes in the temperature environment and occupant comfort levels. Based on the results, the suggested control mechanism effectively maintains occupant comfort while consuming less energy than traditional HVAC systems. Reference [114] proposes an optimal control strategy for HVAC systems in building energy management. Swarm intelligence was used in the control approach to decide how much energy should be sent to each piece of HVAC equipment. Both the building model and HVAC equipment model were created in order to analyze how the functioning of HVAC systems affects the interior environment. To simulate real-time control in a single building, a case study was carried out. In this study, the author conducted simulations in both cold and hot weather to evaluate the control abilities of the heating and cooling units in the HVAC system. Moreover, the simulations were carried out over a 24 h period, and variations in the indoor temperature, CO_2 concentration, and energy consumption were recorded. The simulation revealed the effectiveness of the suggested control technique in attaining energy economy while preserving interior comfort.

Adaptive Control

In non-linear control systems, adaptive control is a powerful method used to manage processes with changing dynamics and stochastic disturbances.

Adaptive control systems provide optimal control performance, even in the presence of uncertainty, by continually modifying the controller settings based on real-time information about the system's characteristics. It can always attain or maintain the intended level of control system performance, even if the parameters of the installed dynamic model are unknown or time-varying [115].

In the context of building HVAC systems, adaptive control refers to a control method that can adapt to changing conditions and uncertainties in the system with the goal of improving its performance.

Reference [116] presents an adaptive control technique for residential heating, ventilation, and air-conditioning (HVAC) systems to support grid services. This study uses a method that includes both the time-varying characteristics of a thermal building's behaviors and the prevailing weather conditions.

3.3.3. Intelligent Control Strategies

Fuzzy Logic (FL)

Fuzzy logic is a methodology that utilizes human reasoning and a linguistic model to address complex and integrated systems without relying on complicated mathematics. The methodology involves creating membership functions and rules to model human knowledge and reasoning about the system without requiring a mathematical model. In contrast to traditional controllers and advanced controllers, such as MPC, fuzzy logic is based on human knowledge and the behavior of the system, making it a more intuitive and flexible approach [117].

The basic idea underlying fuzzy logic control is to represent input variables, including the pressure, humidity, or temperature, as fuzzy sets with membership functions that define their degree of membership to various language words, like "high", "low", "hot", or "cold". The fuzzy logic controller then generates an output that regulates the system using a set of fuzzy IF-THEN rules based on expert knowledge about the system. Finally, the fuzzy output is transformed into a crisp output using a defuzzification approach, such as centroid, maximum, or weighted average, in the defuzzification stage.

Fuzzification, fuzzy inference, and defuzzification are the three basic processes in the fuzzy logic control process [118]. The fuzzification process converts the crisp input values to fuzzy ones [118]. To transfer the input values to a degree of membership in the range of [0, 1], membership functions such as gaussian distribution triangle, bell functions, trapezoidal and sigmoidal functions are used. The next stage is to use a fuzzy inference system to map fuzzy values to distinct fuzzy values by using fuzzy IF-THEN rules and logical operations. There are two types of fuzzy inference systems: Mamdani and Sugeno. The first type is utilized for all kinds of systems, and the second one is mostly employed for dynamic non-linear systems. The collection of the linguistic output values from the previous phase is employed in the defuzzification procedure, giving a single crisp value as an output.

Several studies have utilized fuzzy logic to optimize energy utilization and cost savings in HVAC systems. In this section, we will provide a literature review that covers the implementation of fuzzy logic control in this area.

The usage of a fuzzy logic control technique in household appliances is suggested in reference [119] to minimize energy consumption and costs; the authors model and analyze the energy consumption of household appliances, including HVAC systems, electric water heaters (EWHs), and lighting, using a fuzzy logic controller model (FLC) that can optimize energy use depending on the current conditions and user preferences. The model is validated using simulations in MATLAB Simulink, and the results reveal that the fuzzy logic control approach may save significant amounts of energy and money when compared to traditional control methods.

In [120], the authors propose a fuzzy logic as a soft control technique to regulate the speed of an HVAC evaporator fan in order to maintain the ambient temperature at necessary set points. They integrate the occupants' preferences as dynamic elements of the control technique without considering any features of the building envelope, which would enable the designed system to function and be applied in various structures. The results demonstrate that it is possible to maintain an ambient temperature with significantly reduced energy usage by controlling the evaporator fan speed with a fuzzy logic controller.

The writers of reference [121] worked to develop a smart home energy management system (HEMS) for managing residential appliances with the intention of reducing electricity bills and power usage while ensuring customer comfort. The study employed Simulink/MATLAB to model and analyze many commonly utilized home appliances, including lighting; heating, ventilation, and air-conditioning (HVAC); and electric water heaters (EWHs). They used a fuzzy logic controller (FLC) within the HEMS to predict energy consumption and conduct a cost analysis during peak, off-peak, and combination hours. Then, they proposed a particle swarm optimization (PSO) algorithm to optimize the FLC's performance and ensure optimal cost and power consumption. The results demonstrated that, for HVAC, EWH, and dimmable lighting, the newly designed FLC controller considerably lowered the expenses and energy usage during peak hours. The modified fuzzy PSO controller increased energy savings and decreased power usage. The authors of reference [122] explored how to improve thermal comfort while maintaining or reducing energy usage in HVAC systems. They created and developed a single zone building model and HVAC model using EnergyPlus software and the Transient system simulation tool, respectively. Also, Simulink was used to construct both traditional on/off controllers and fuzzy logic. Then, the building control virtual Test Bed was used to link the simulation models. In terms of thermal comfort, the fuzzy HVAC controller performed better than the on/off controller, resulting in a 33% decrease in occupant dissatisfaction and a 50% decrease in non-comfort hours. On the other hand, the energy consumption results were comparable for both controllers. The authors concluded that fuzzy logic control has the potential to be effective in HVAC systems. Table 4 presents some building control work using fuzzy logic.

Table 4. Fuzzy logic control.

Control Method	Ref.	Results	Software	Advantages	Disadvantages
Fuzzy Logic	[119]	Reductions of 21.75%, 30.77%, and 41.96% in energy consumption by using FLC for the HVAC, EWH, and dimmable lamp, respectively.	MATLAB SIMULINK, Fuzzy logic Toolbox	Energy Savings, cost reduction, improved efficiency, increased comfort.	Requires turning of fuzzy controller, has limited applicability to specific appliances and conditions.
	[120]	Significant reduction in energy consumption by controlling the evaporator fan speed	MATLAB, Fuzzy Toolbox	Maintains ambient temperature at required set points. Reduces energy consumption. Improves thermal comfort.	Complexity in designing fuzzy control rules. Requires expertise in fuzzy logic control.

Table 4. *Cont.*

Control Method	Ref.	Results	Software	Advantages	Disadvantages
Fuzzy Logic	[121]	Reduce the cost and energy consumption for peak period by 19.72% and 20.34%, by 26.71% and 26.67%, and by 37.5% and 33.33% for HVAC, EWH, and dimmable lamps, respectively, using FLC controller	Simulink/MATLAB	Provides energy utilization estimation and cost analysis. Achieves significant cost and energy savings during peak periods. Optimizes the schedule operation of home devices.	Requires modeling and analysis of household loads. Complexity in designing fuzzy-PSO controllers. Need for expertise in fuzzy logic and particle swarm optimization.
	[122]	Reduce the annual mean percentage of dissatisfied occupants by 33%; reduce the non-comfort hours by more than 50%	Energy Plus, Simulink, Building Control Virtual Test Tool, Control Virtual Test Bed, BCVTB	Enhances thermal comfort provision for building occupants. Promising method for dealing with multivariable control problems.	Real-life implementation needed to verify the potential of fuzzy control in HVAC applications.

Deep Learning Based on Artificial Neural Network (ANN)

An artificial neural network (ANN) is an information processing algorithm inspired by the human brain and its learning process. It consists of interconnected neurons organized in layers (input, hidden, and output) that process information, as presented in Figure 12. ANNs use network weights and transfer functions to compute data based on inputs. They possess adaptability through self-turning and are increasingly applied for the advanced thermal control of buildings. ANNs have advantages, such as the ability to handle a large number of input variables and a large amount of data, allowing for the modeling of complex non-linear systems. Through training, ANNs can simulate and solve complex non-linear functions [123].

Reference [124] focuses on utilizing artificial neural networks (ANNs) to predict the ideal start time for a building's heating system; to achieve this, the researchers developed algorithms to estimate a room's air temperature and used backpropagation learning to design an ANN model. They collected learning data by simulating various building conditions and predicting the room's air temperature. The results of the study demonstrate the effectiveness of the optimized ANN model. In a variety of techniques, artificial neural networks (ANNs) have been employed in building energy control [125].

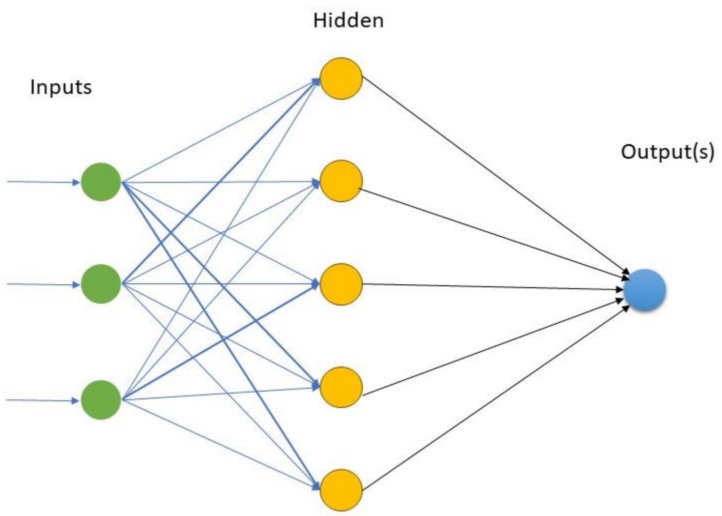

Figure 12. Artificial neural network [126].

Reference [127] presents a comprehensive overview of the use of artificial neural networks (ANNs) in building energy analysis (BEA). The study includes three decades of research, concentrating on various domains such as water heating and cooling systems, HVAC system modeling, heating and cooling load prediction, indoor air temperature prediction, and building energy consumption prediction. The majority of existing studies have focused on predicting the interior air temperature and building energy use for a detailed understanding of the concept.

Reinforcement Learning (RL)

Reinforcement learning (RL) is a type of machine learning, as shown in Figure 13, that focuses on solving control or sequential decision-making problems [128]. Contrary to unsupervised learning, which uses unlabeled data without feedback, and supervised learning, where the agent immediately receives an input on how accurate its predictions were, RL falls in the middle since it receives delayed feedback. The concept of reinforcement learning is based on the learner or agent, which learns to map situations to actions to maximize a delayed reward signal. It does not require a teacher to provide explicit instructions, but instead makes decisions though trial and error, recognizing the rewards obtained from the environment it interacts with [129].

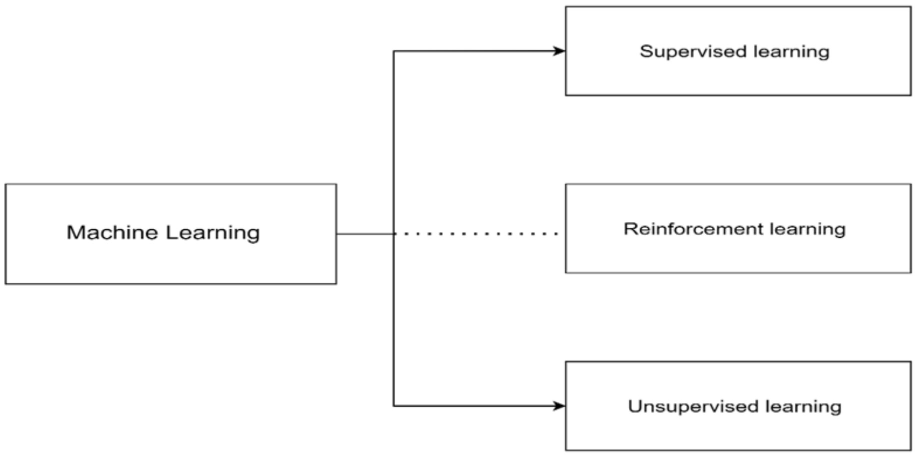

Figure 13. Machine learning types [130].

Reference [131] proposes a reinforcement learning model for the energy-efficient control of thermal comfort in a multi-zone residential HVAC, improving comfort prediction and reducing energy consumption. Also, [132] investigates the application of deep reinforcement learning (DRL) to optimize building HVAC systems and reduce energy costs while maintaining room temperature. The simulations demonstrate the effectiveness of the DRL compared to traditional strategies.

Transfer Learning (TL)

Transfer learning is a subset of machine learning. The fundamental concept behind transfer learning is to apply previously learned knowledge from one task to improve the performance in another task that shares similarities.

TL is used in the building sector for two mean reasons: prediction and occupancy detection and activity recognition [133]. Using transfer learning for HVAC control in buildings has several advantages, including better performance [134,135], the ability to transfer knowledge from one building to another with minimal effort [136,137], and a reduced training time [138]. The use of transfer learning in HVAC control for buildings has been studied in a few papers; in [139], transfer learning was applied to environmental sensor data to predict the occupancy status in an educational building. The methodology employed in this study included the use of two deep learning models: a staked long short-term memory (LSTM) model and a sequential deep model. Then, the authors applied transfer learning on top of them. In terms of accuracy and outcomes, the stacked LSTM model combined with the transfer learning framework predicted the occupancy status with the best accuracy. The findings demonstrated the usefulness of transfer learning for occupancy prediction modeling, especially when limited historical training data are available. In [140], the authors examined the challenge of HVAC load forecasting with limited available data. In order to solve this problem, they presented a combination of simulation software and the transfer learning approach. Their research shows that this novel methodology surpasses traditional load forecasting approaches by a remarkable 10% in accuracy.

4. Discussion

In the dynamic field of building management systems, the deployment of sophisticated control techniques plays a pivotal role in optimizing operational efficiency and enhancing occupant comfort. Among these techniques are conventional controls, like proportional–integral–derivative (PID) controllers; advanced controls, like model predictive control (MPC); intelligent controls, like fuzzy logic; and machine learning (ML), and each one is distinguished by its unique capabilities and applications.

PID controllers have been widely utilized in building management due to their efficiency in linear systems. They are known for their simplicity and consistency. Because of their uncomplicated approach to control, they are a popular choice for simpler settings. However, they have limitations in complicated, non-linear systems and require manual tuning, which can be time-consuming and requires technical competence [141].

Differently, model predictive control (MPC) is a sophisticated solution, excelling in scenarios characterized by non-linear dynamics and strict regulatory constraints. In contrast to the traditional proportional–integral–derivative (PID) system, which operates on a simpler feedback loop paradigm and is esteemed for its ease of implementation and robustness in stable environments, MPC adopts a forward-looking approach. It employs predictive models to anticipate future system states, demonstrating remarkable skill in managing non-linearities and constraints, which are achievements that PID control does not achieve as effectively [142]. MPC marks a significant advancement in building management systems with its ability to forecast the future states of a system using a comprehensive system model. It excels at managing complex, dynamic systems by minimizing a specified cost function and considering multiple constraints and disturbances. MPC is particularly effective in scenarios requiring predictive adjustments and precise control, outperforming traditional methods like PID in energy efficiency and adaptability. Nevertheless, its high processing demand and implementation complexity present challenges, particularly in real-time applications [143].

Since each control method has its advantages and disadvantages, it is crucial to evaluate the performance of control algorithms rigorously. This evaluation must specify the parameters and comparative measurements used. Typically, researchers compare the performance of their purposed controllers with existing ones, using one or two performance measures, as mentioned above. These measures help to determine the superiority or effectiveness of one method over another based on concrete performance criteria that are relevant to the specific field of application [144]. The performance criteria include the following:

- Load management;
- Efficiency;
- Error reduction;
- Transient responsiveness;
- Decision variable management;
- Operational efficiency;
- Set-point regulation;
- Operational stability;
- Environmental quality;

- Computational efficiency.

These measures help to determine the superiority or effectiveness of one method over another based on concrete performance criteria relevant to the specific field of application [145].

Reference [146] explores the effectiveness of model predictive control (MPC) strategies in managing building temperature control in multi-zone environments. It compares the performance of decentralized, distributed, and centralized MPCs with conventional on/off and P/PI controllers. The study finds that conventional controllers, such as PI, operate independently for each zone and do not consider the thermal interaction between adjacent zones, leading to lower comfort levels. Decentralized MPC offers slight improvements by optimizing transition phases between occupied and non-occupied periods but does not fully integrate thermal coupling into its model. Centralized and distributed MPC methods significantly improve thermal comfort and reduce energy consumption by 36.7% and 13.4%, respectively. Distributed MPC is particularly advantageous for large systems due to its lower computational demand and efficient one-step communication algorithm.

In low-energy residential structures, reference [147] investigates how model-based predictive control (MPC) may be used to optimize supply fluid temperature for water-based underfloor heating. The goal is to use numerical optimization to keep interior temperatures within a given comfort range by projecting future heat demand. A simple two-node model and a comprehensive numerical control volume model are the two models used in the study. Similar to the more sophisticated model, the simpler model delivers good accuracy. In a single room with precise heat demand prediction, the control method's efficacy is evaluated. The findings demonstrate that, especially when periods are set at two hours, the optimal supply fluid temperature Is reasonably stable.

In buildings with variable air volume (VAV) systems, reference [148] focuses on enhancing the indoor air quality (IAQ) and temperature management—achievements that are not possible with conventional ventilation control techniques. In order to regulate the temperature and ventilation in various zones of a building, this study proposes a Multiple Input Multiple Output (MIMO) controller that is used in conjunction with the Model predictive control (MPC) method. This controller is made with respect to ventilation standards and adheres to the ventilation rate process, as outlined in ASHRAE 62.1. Simultaneous temperature and ventilation management depends on the MPC system's capacity to regulate input and output constraints.

The authors of [149] focus on harnessing solar energy in residential buildings using predictive control to manage a radiant floor heating system and a solar heat pump for thermal storage. Simplified models are essential for optimizing these systems. The results show that model-based predictive control can effectively regulate heating in solar-rich environments and that supervisory control significantly improves solar system performance. The research highlights the potential for integrating solar energy into home energy management and suggests avenues for further exploration.

A new control system for HVAC units isIIed in [150] using support vector regression (SVR) to build a dynamic model, which is then used in a model predictive controller (MPC). This approach has been experimentally shown to outperform a traditional neural fuzzy controller, particularly in terms of reference tracking and steady-state error reduction. When using a neural fuzzy controller, the steady-state errors for room temperature and humidity were 0.2 °C and 1.5%, respectively. In contrast, the SVR-based MPC controller reduced these errors to 0.09 °C and 0.4%, representing improvements in accuracy of around 100% and 400%. The research also highlights the advantages of SVR for the accurate modeling of non-linear systems and the effectiveness of MPC in operational control. This comparison highlights the superior accuracy and efficiency of an SVR-based MPC system compared to the fuzzy neural method, representing a significant advance in HVAC control techniques for home energy management and suggesting avenues for further exploration.

In the context of HVAC systems, reference [151] compares data-driven model predictive control (MPC) with conventional (two-position) on/off control. Specifically, it looks at how to manage the energy usage of a single-stage heat pump air conditioner. The study uses the BRITE (Berkeley Retrofitted and Inexpensive HVAC Testbed for Energy Efficiency) platform to operate an air conditioner in a computer lab and record the temperature and energy consumption. The learning-based MPC system implemented in this study performed significantly better than two-position control, with a 30–70% reduction in energy consumption. This performance is attributed to the MPC system's ability to adapt to different occupancy levels and effectively manage the air conditioner's transient and stable power consumption. The study highlights the MPC's effectiveness in conserving energy and maintaining comfortable ambient temperatures by dynamically adjusting cooling based on the estimated occupancy and by taking into account the heat pump's electrical behavior. This approach enables more nuanced and energy-efficient operation than the simpler on/off control method.

With a focus on model predictive control (MPC), reinforcement learning (RL), and a hybrid technique called reinforced model predictive control (RL-MPC), an article titled "Comparison of Optimal Control Techniques for Building Energy Management" investigates the efficacy of various control systems in building energy management. Reference [152] shows that MPC typically performs better than other approaches when using the Building Optimization Testing (BOPTEST) framework, especially when the prediction horizon is closely aligned with the building's time constant. In realistic architectural contexts, reinforcement learning (RL), especially in its model-free version, performs poorly, making it difficult to sustain comfort levels and falling short of MPC. The study found that, while RL has difficulties in controlling the temperatures of buildings directly, hybrid strategies like RL-MPC, which combine MPC with machine learning methods, have promise for efficient energy management.

The application of fuzzy logic controllers in HVAC systems is covered in reference [153], along with a comparison between them and conventional PID controllers. It was discovered that FLCs had fewer supply air temperature variations and superior integral control quality indicators (IAE, ISE, ITAE, and ITSE) by at least 27.4%. An average of 36% less daily mean square error (MSE) was observed, which improved passenger comfort and likely resulted in lower energy use. Energy usage was 12.7% less than that with an untuned PID.

To this end, this section concludes that advanced control methods, such as model predictive control, are the most widely used of the alternative approaches in combination with AI, although they present certain challenges, particularly with regard to their complexity.

However, connecting Internet of Things (IoT) technologies to building management systems, alongside improved control approaches, enables the development of intelligent, more efficient, and responsive buildings. The integration of IoT technology with advanced control strategies will revolutionize the field of building automation, presenting promising prospects for innovation and improvements in energy efficiency, system reliability, and occupant satisfaction.

5. Hardware Implementation

Smart homes, as presented in Figure 14, automate and improve various aspects of our living environment, such as energy management, thermal comfort, and security [154]. They achieve this by integrating a sophisticated network of devices connected via the Internet of Things (IoT) [155]. The equipment in these homes can communicate with each other, creating a synchronized network, and can also be remotely controlled by occupants via digital interfaces, such as mobile apps, thanks to a number of connection techniques, including WIFI and Bluetooth, for example [154]. The aim of smart homes is to increase energy efficiency, comfort, and safety for occupants. However, Domotics, and IoT technology are transforming the way we live, creating smarter homes and improving comfort; thus, integrating embedded systems with IoT has promising commercial potential, but the challenge is to balance energy consumption and system efficiency while ensuring user comfort during operation [156].

The concept of the Internet of Things (IOT) enhances home automation management by combining automation, computing, and communication technologies, enabling the interconnection and real-time control of physical devices, thus improving the quality of comfort, safety, and well-being within the residential environment.

In [157], the authors focus on a comprehensive implementation strategy for an Internet of Things (IoT) smart home system that exploits ZigBee/GPS technology. The paper focuses on why ZigBee wireless communication is suitable for smart home systems and on architectural plants for software and hardware components.

In [158], the authors present "ZiWi", a reasonably priced Home Automation System (HAS) that makes use of the IOT fog computing paradigm to improve communication between ZigBee and WiFi devices in smart homes. With an emphasis on effective, seamless communication between WiFi and ZigBee technologies in the crowded 2.4 GHz band, ZiWi makes use of the current developments in wireless protocols and cloud services. The system's design makes use of local gateways that are installed on embedded devices to handle user interface, communications, and data storage; WiFi is used for actuators, while the preliminary results show ZiWi's effectiveness in reducing latency compared with the other cloud services evaluated, and they highlight the need to mitigate the ZigBee–WiFi cross-interference and consider the impact of encryption mechanisms on node energy consumption. In addition, ZiWi technology facilitates system scalability, provides a user-friendly GUI via OpenHAB, and uses MQTT to solve compatibility issues associated with different protocols and standards in the home automation field, while also highlighting the importance of using the cloud computation approach to provide real-time or near-real-time responses and enhance security. Reference [159] takes an in-depth look at the complex IoT landscape, focusing on the dilemma of networking technologies such as ZigBee and Z-Wave in smart home deployments. It highlights the need to create a fair, cost-effective, and user-friendly protocol while resolving the difficulties of interoperability between various devices and platforms. As a part of the study into the development of future self-sufficient, energy-intensive homes, a comprehensive cloud-centric IoT framework is suggested to bridge the gap between existing smart home applications and the IoT environment [159]. Furthermore, the LoRa Building and Energy Management System (LoBEMS), an innovative energy management platform optimized for energy consumption, is presented in [160]. Rooted in an IOT component, including system and platform integration trends, it aims to merge several factors. The LoBEMS can be easily integrated into any building structure, including those with existing solutions. It controls large energy consumers, mainly cooling and heating systems. The implementation of the LoBEMS in a pre-school resulted in substantial energy savings of 20%. There are several other protocols for communication that are available, including Bluetooth [161], UWB [162], wireless USB [163], and Wi-Fi [164,165].

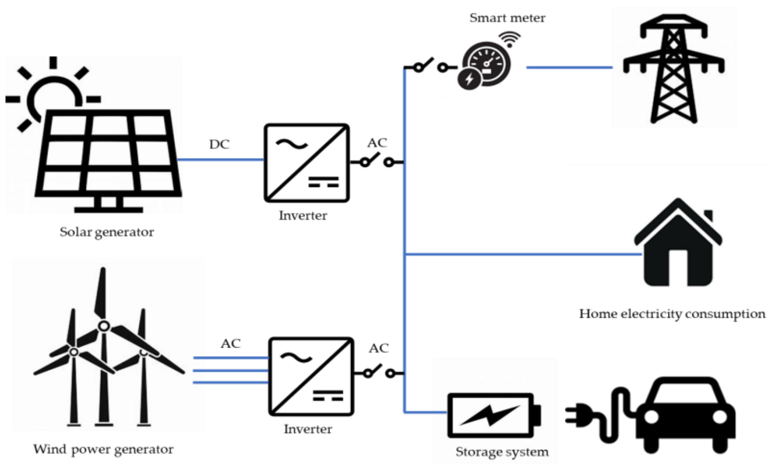

Figure 14. Smart home [159].

Moreover, heating, ventilation, and air-conditioning (HVAC) systems in smart buildings will be controlled by a predictive control model (MPC) using an Internet of Things (IOT)-based architecture. In [166], the proposed system includes smart sensors and actuators, an interconnected gateway, a control unit, a database server, and user-friendly dashboards, all of which are presented in Figure 15 with the aim of maximizing both indoor thermal comfort and energy consumption. This allows the system to be configured remotely and monitors environmental indicators in real time. A notable aspect is its holistic approach to HVAC management, which integrates IOT components for practical deployment while also including the issue of MPC optimization for system control.

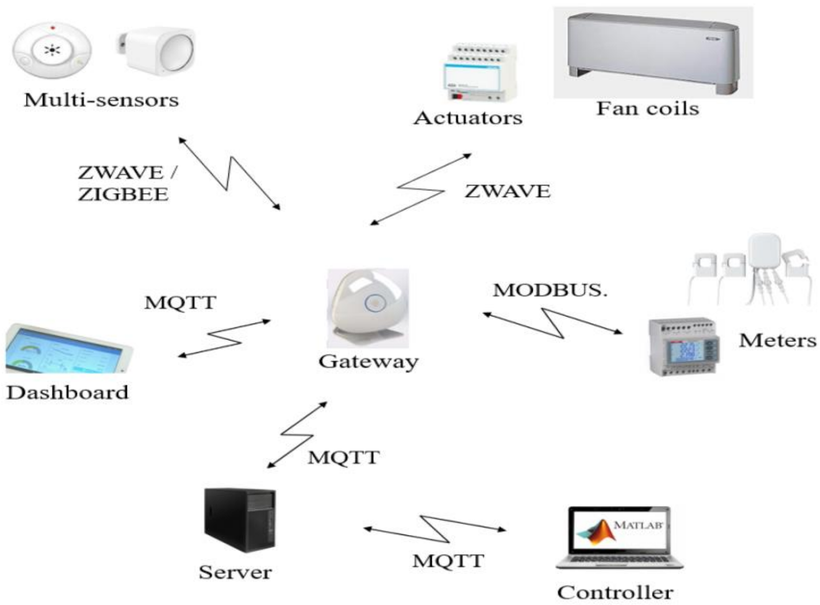

Figure 15. Deployed experimental system architecture [166].

The results were higher than those of conventional thermostats, delivering significant energy savings while maintaining indoor comfort in the presence of various disturbances. However, its limitations include the absence of a deep cost analysis and data uncertainty. In a similar view, reference [167] aims to examine the difficulties and constraints involved in using model predictive control to control energy consumption in buildings, especially when taking into account the diverse characteristics of buildings and the considerable time and costs involved in developing control-oriented physical models.

This study presents a new method that combines data-driven predictive control (DPC) with the Internet of Things (IOT), thus avoiding the need for detailed physical modeling. By creating a cloud-based Supervisory Control and Data Acquisition (SCADA) building system framework, the research investigation aims to control a building's energy under a four-tier building energy IOT architecture.

6. Conclusions

While renewable energies are sure to have a great impact by reducing greenhouse gas emissions, it is far from easy to fully switch from conventional sources of energy due to the various challenges still facing renewable energy utilization, especially in the residential sector. This is due, on the one hand, to the fact that it accounts for a significant proportion of energy consumption and, on the other hand, to the possibility of integrating several renewable sources, namely photovoltaics, micro wind turbines, and geothermal energy, among others. As a result, this sector must undergo a major transformation, as it is the second largest consumer of energy in Morocco. However, the implementation of several smart technology techniques using renewable energy requires complex computations.

Moreover, accurate models of HVAC systems, for example, are not completely accurate, and might be unpredictable when facing dynamic real-life settings.

This study consisted of a comprehensive analysis of 167 research publications on control strategies and techniques in the building sector. The focus was on techniques for reducing energy consumption while maintaining thermal comfort. We examined the regulations and standards governing this industry, as well as the incorporation of the Internet of Things into the hardware implementation as a solution. A comprehensive analysis of different control strategies was carried out. Specifically, it was discovered that sophisticated control systems, such as MPC, were the most powerful because they could effectively include an accurate mathematical model of the controlled region. This integration enables the creation of a robust and flexible control system facilitated by an objective function that precisely specifies the parameters that need to be reduced or maximized, particularly when combined with artificial intelligence. This combination not only facilitates the accurate forecasting of energy requirements, but also enables more intelligent energy management, both in terms of production and consumption. In addition, this approach contributes to the design of intelligent buildings that meet all current and future requirements, marking a significant step towards improving the energy performance of buildings. Our future objective is to use the MPC predictive control technique, coupled with an artificial intelligence model, to regulate HVAC systems. This would effectively reduce energy usage and maintain optimal thermal comfort.

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Abbreviations

MIQP	Mixed Integer Quadratic Programming
AI	Artificial Intelligence
ANN	Artificial Neural Network
FL	Fuzzy Logic
HVAC	Heating, Ventilation, and Air-Conditioning
IOT	Internet of Things
ISO	International Organization for Standardization
LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
MIMO	Multiple-Input Multiple-Output
MPC	Model Predictive Control
PID	Proportional Integral Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
RL	Reinforcement Learning
TL	Transfer Learning
TR	Thermal Regulations

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