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Review

Review on Advanced Storage Control Applied to Optimized Operation of Energy Systems for Buildings and Districts: Insights and Perspectives

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Citation: Ferrara, M.; Bilardo, M.; Bogatu, D.-I.; Lee, D.; Khatibi, M.; Rahnama, S.; Shinoda, J.; Sun, Y.; Sun, Y.; Afshari, A.; et al. Review on Advanced Storage Control Applied to Optimized Operation of Energy Systems for Buildings and Districts: Insights and Perspectives. *Energies* **2024**, *17*, 3371. https://doi.org/10.3390/en17143371

Academic Editor: Kian Jon Chua

Received: 30 May 2024
Revised: 21 June 2024
Accepted: 5 July 2024
Published: 9 July 2024

Abstract: In the context of increasing energy demands and the integration of renewable energy sources, this review focuses on recent advancements in energy storage control strategies from 2016 to the present, evaluating both experimental and simulation studies at component, system, building, and district scales. Out of 426 papers screened, 147 were assessed for eligibility, with 56 included in the final review. As a first outcome, this work proposes a novel classification and taxonomy update for advanced storage control systems, aiming to bridge the gap between theoretical research and practical implementation. Furthermore, the study emphasizes experimental case studies, moving beyond numerical analyses to provide practical insights. It investigates how the literature on energy storage is enhancing building flexibility and resilience, highlighting the application of advanced algorithms and artificial intelligence methods and their impact on energy and financial savings. By exploring the correlation between control algorithms and the resulting benefits, this review provides a comprehensive analysis of the current state and future perspectives of energy storage control in smart grids and buildings.

Keywords: thermal storage; energy storage; electric storage; model predictive control; artificial intelligence

1. Introduction

In the context of the ongoing energy transition toward extensive utilization of multiple renewable energy sources, energy storage systems are essential for managing the variability of renewable energy supply and aligning it with the fluctuating profiles of energy demand [1]. Energy storage not only facilitates this energy match but also enhances the integration of renewable multi-energy systems, thereby promoting the transition toward decarbonized or zero-emission buildings [2]. The deployment of such systems in buildings has been proven relevant in reducing greenhouse gas emissions and achieving sustainable energy goals [3].

However, the control strategies for these storage systems are complex, requiring the optimization of numerous interrelated variables and the management of uncertain inputs. This complexity requires advanced control techniques to ensure the optimal operation of multi-energy systems so that they exploit their full energy efficiency potential [4]. The significant body of research on this topic highlights its importance, with numerous studies focusing on the optimal integration of energy storage in the design and operation of energy systems for buildings and districts.

In 2015, a notable review by Yu et al. [5] on control strategies for Buildings Integrated with Thermal Energy Storage (BITES) exemplified the depth of research in this area. Following the categorization of control techniques derived by Afram et al. [6], reported in Figure 1, this review explored various control techniques, discussed their strengths and weaknesses, and anticipated the advancements in control methods that have emerged in recent years. The authors highlighted the potential of Model Predictive Control (MPC) and AI-based methods, which, although nascent at the time, have since been considered to be promising.

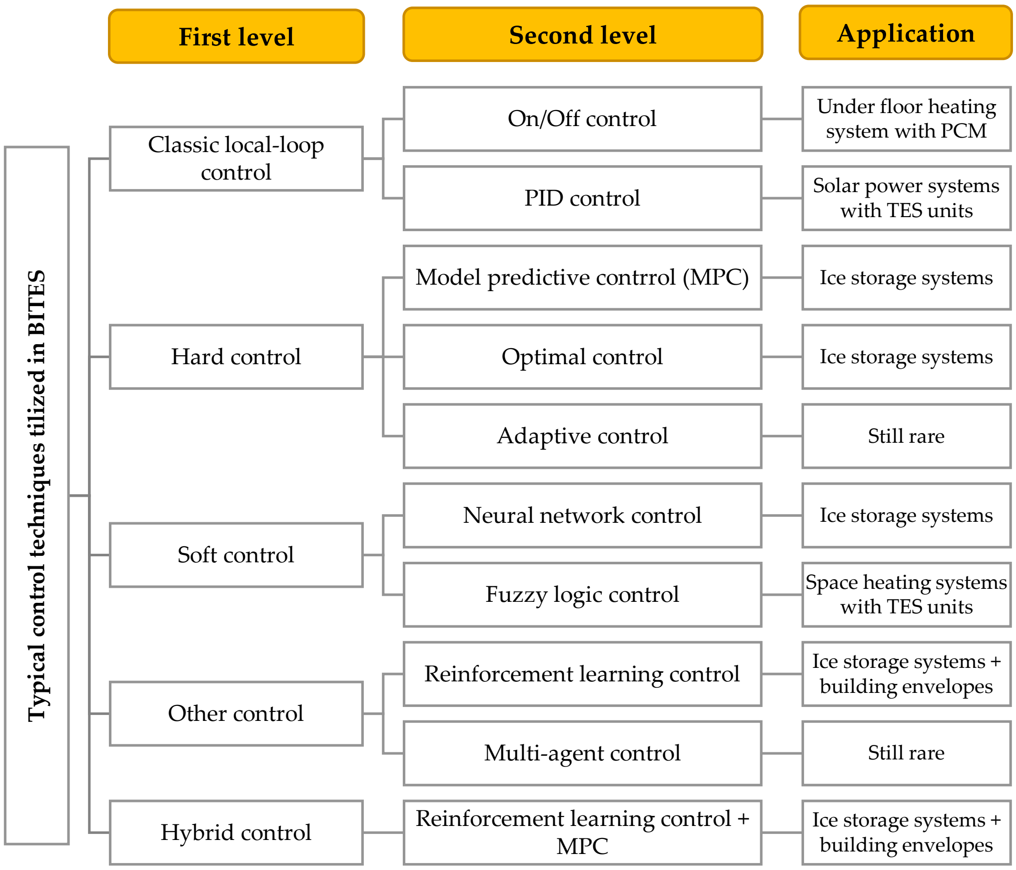

Figure 1. Classification and typical applications of control techniques utilized in BITES (adapted from [5]).

In subsequent years, driven by rapid advancements in research, several review studies on advanced control strategies using prediction models were published. In 2017, Thiebelmont et al. [7] focused on studies enhancing storage performance through predictive control strategies based on weather forecasts. Similarly, in 2021, Tarragona et al. [8] reviewed the application of model predictive control (MPC) techniques to thermal energy storages, excluding electrical energy storages.

During the same period, other reviews concentrated on MPC applied to specific energy storage technologies, such as phase change materials (PCM) [9]. Additionally, Gholamzadehmir's 2021 review explored MPC for HVAC system control in smart buildings [10], following the 2018 review by Sanchez Ramon et al. [11] that addressed the integration of storages in smart buildings. Furthermore, a review dedicated to storage control in microgrids was published in 2021 [12], filling a previous gap by focusing on the control of electrical storages and expanding the perspective from building-scale to district-scale applications.

The analysis of the latest review related to the topic reveals that the current decade has been crucial for the development of innovative methods for energy storage control based on advanced computational techniques, mainly based on artificial intelligence. Therefore, it is believed that such a massive and fast development requires a comprehensive review of the latest results and trends emerging from studies published in the most recent years on the control of energy storage (both thermal and electrical) integrated into multi-source multi-energy systems for the built environment.

An updated classification of storage control techniques based on the latest developments is required, including, but not limited to, the support of the different declinations of artificial intelligence for all the available control strategies, regardless of whether they rely on predictive models or not. Another crucial point requiring a critical review is the applicability of the different control methods in practice, based on the analysis of the relationship between the control (the software) and the type of storage (the hardware), results and criticalities emerging from experimental studies, or real case studies.

This paper aims at filling such gaps by the identification and review of recent studies concerning the control of energy storage integrated into systems for buildings or groups of buildings that are not only purely theoretical or numerical studies but where some experimental activities were carried out or where analysis is conducted based on real case studies. This is particularly important to evaluate the effectiveness of the control strategies against real measurements. Thus, a systematic review process was implemented and aimed at identifying the latest advancements in energy storage control, the emerging trends, and the role of AI in shaping such trends, as well as future perspectives.

2. Methodology

2.1. Papers Selection Process and Inclusion in the Review

Following a systematic review process based on the previously identified research question, extensive literature research was conducted using the Scopus® database in early 2024. The search was performed by considering titles, abstracts, and keywords. The query used was the following: TITLE-ABS-KEY (building energy storage control) AND TITLE-ABS-KEY (experimental OR real OR experiment OR case-study) AND PUBYEAR > 2014 AND LIMIT-TO (LANGUAGE, "English").

This extensive search yielded 426 papers, which were systematically filtered following the methodology outlined in Figure 2, similar to the approach used by Song et al. [13], adopting a PRISMA statement flowchart [14]. Initially, the identification pre-screening process resulted in a set of 408 papers. Title and abstract screening then reduced this number to 147 papers that were considered relevant to the scope of the review based on their abstracts and thus were included for further statistical description (Section 2.2) and analysis (Section 3.2). Subsequently, a full-text screening narrowed the selection to 56 papers that fully aligned with the review's objectives. These papers were analyzed in greater detail in Sections 3.3 and 3.4, providing the foundation for the discussion and future perspectives sections.

2.2. Description of the Dataset

To comprehensively understand current trends in advanced storage control for optimizing energy systems in buildings and districts, a preliminary statistical analysis of the literature was conducted based on the year of publication, the scale of the study, the type of storage, and the nature of the study. These characteristics were selected to provide insights into the development of research over time, the scope and focus of studies, the variety of storage technologies examined, and the methodologies employed.

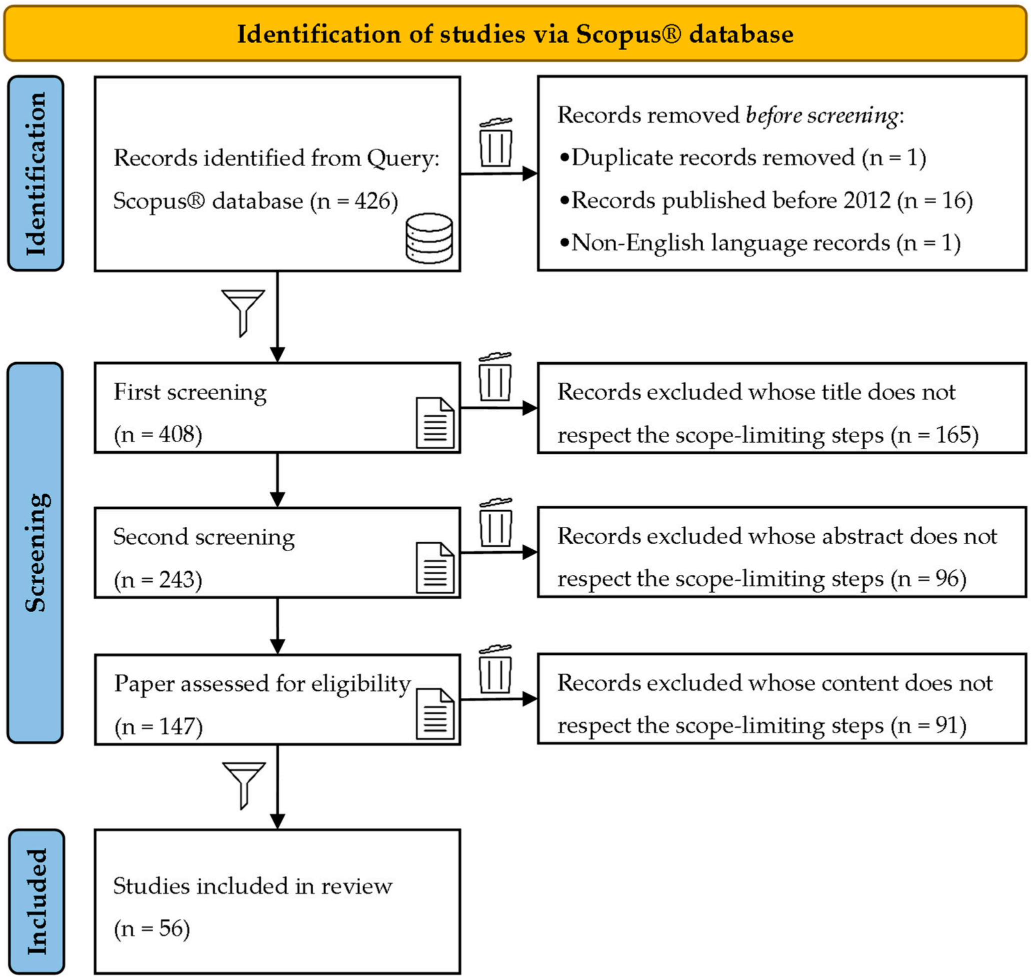

Figure 2. The process of creation of the dataset for the present review, adopting a PRISMA statement flowchart.

Figure 3a shows that publications have increased significantly since 2017, peaking in 2019 and 2020. The surge in publications during 2019 and 2020 can be attributed to the significant global push toward renewable energy adoption. This was driven by a number of factors, including the decreasing costs of renewable technologies and supportive policies, as well as the economic recovery packages that were implemented following the COVID-19 pandemic and which prioritized green investments. The distribution by scale (Figure 3b) indicates that 57% of studies focus on building-scale applications, with fewer studies on systems (16%), districts (17%), and components (10%), highlighting a primary interest in optimizing building energy management.

In terms of storage type (Figure 3c), active thermal storage is most prevalent (51%), underscoring its critical role in managing building energy. Active electrical storage is covered in 23% of the papers, while passive storage technologies account for 22%, and hybrid storage systems constitute a small fraction (4%).

Regarding the nature of the studies (Figure 3d), 62% are simulation-based with real data, indicating a preference for modeling and optimization. Hybrid studies represent 24%, and purely experimental studies make up 14%, demonstrating a balanced approach to validating models with empirical data.

Overall, this statistic reveals significant trends and focus areas in the field, emphasizing the importance of building-scale applications and thermal storage solutions. The methodological diversity, especially in the use of real data in simulations, underscores the commitment to ensuring the practical relevance of research. These findings highlight the dynamic nature of the field and the ongoing efforts to develop more efficient energy storage and control systems for sustainable energy management in buildings and districts.

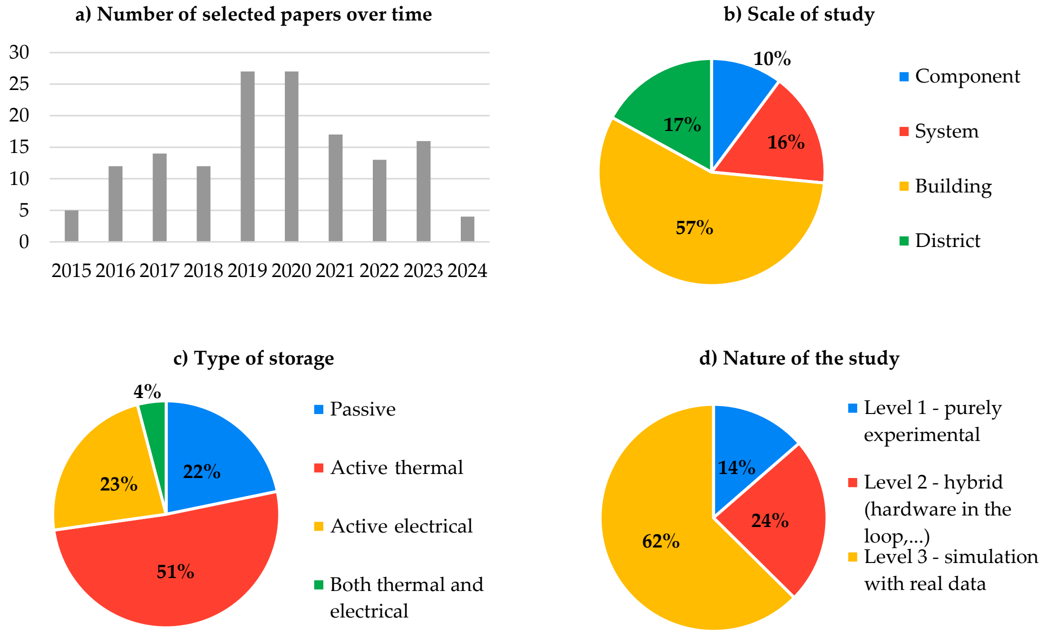

Figure 3. Overview of the 147 papers assessed for eligibility. Year of publication, scale and nature of study, and type of storage included in the study.

3. Results

3.1. An Updated Classification and Taxonomy of Control for Energy Storage in Buildings

Control systems for energy storage in buildings can be categorized based on their methodology and approach. This section presents an updated classification of these systems, which has been summarized graphically in Figure 4. The main objective of utilizing energy storage systems is to achieve energy and cost savings by shifting demand over time. Consequently, control systems for energy storage must account for the temporal operation of each component, understanding how actions from the present are translated into the future.

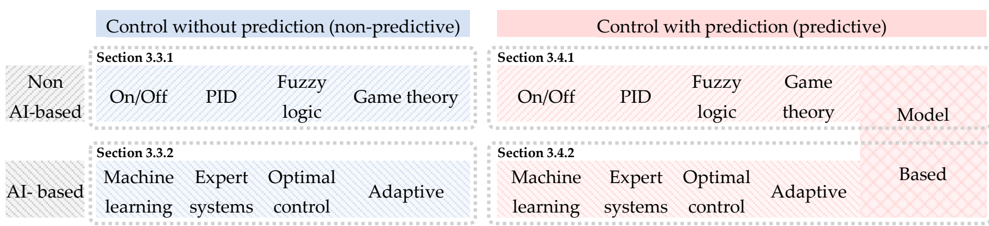

Figure 4. Control systems and methods for energy storage: the proposed updated classification.

In this context, control systems can be broadly divided into two categories: non-predictive control and predictive control. Non-predictive control, such as on/off control or PID control, involves sequential decision-making that does not rely on future predictions. An example is a thermal energy storage system that generates thermal energy at night when electricity prices are low and discharges it during the day when prices are high. This type of control operates based on predetermined schedules without forecasting future demand.

In contrast, predictive control involves forecasting future conditions to optimize system performance. For example, predicting the next day's heat demand and determining the optimal amount of heat to produce in advance exemplifies predictive control. Predictive control is a subset of feedback (closed-loop) control systems, but not all feedback control systems include predictive elements. Therefore, the classification of control systems for energy storage has evolved from the traditional open-loop and closed-loop categories to a more nuanced distinction between non-predictive and predictive control.

Within both non-predictive and predictive control categories, further sub-classifications can be made based on the methods used: classical methods and Artificial Intelligence (AI)-based methods. Classical methods include on/off control, PID control, and fuzzy logic, among others. AI-based methods involve machine learning, expert systems, and adaptive control techniques. While rule-based methods that use conditional decision branching can sometimes be considered AI, they are classified here under classical methods for clarity.

Figure 4 illustrates this updated taxonomy, depicting the hierarchy and relationships between different control strategies for energy storage systems in buildings. This new classification framework aims to better capture the complexity and sophistication of modern control systems, facilitating a more detailed and accurate analysis of their performance and application.

3.2. Relationships between Controls and Applications

The previous classification of control methods is applied to the body of literature assessed for eligibility (147 papers), as depicted in Figures 5–7. Figure 5 shows the distribution of papers according to the two levels of control types. For control without prediction, 85% of studies utilize classical control strategies, such as PID and on/off control. In contrast, 59% of papers involve control with prediction, with classic strategies employed in 35% of these studies. Notably, 60% of studies within predictive control adopt AI-based strategies, while the remaining 5% use hybrid methodologies that combine classical and AI approaches.

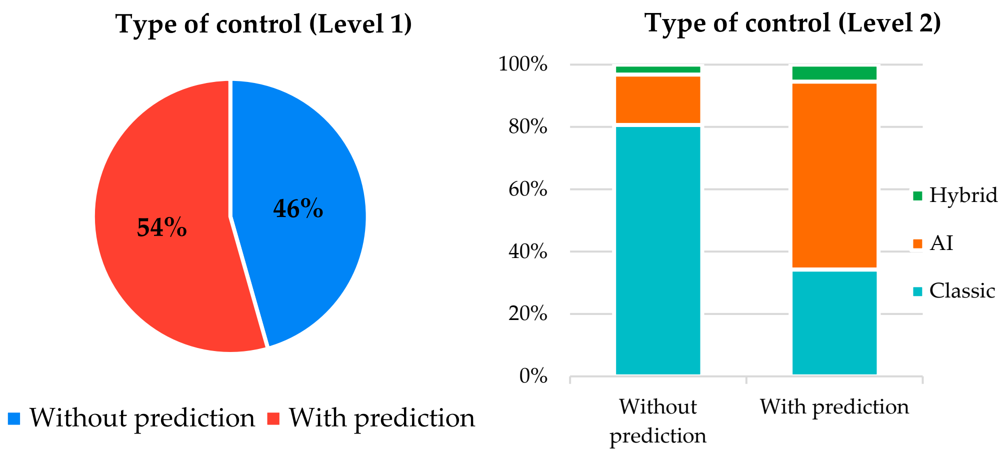

Figure 5. Repartition of papers according to the two levels of control types.

The relationship between the type of storage and the control methods employed is illustrated in Figure 6. Predictive control methods are predominantly used for active thermal and electrical storages. As we progress from passive to active storages, the reliance on classical control decreases, giving way to AI or hybrid control methods. This trend indicates a preference for more sophisticated control mechanisms as the complexity and dynamism of the storage system increase.

Finally, Figure 7 presents the correlation between the scale of storage applications and the type of control methods. The data reveal that larger-scale applications, such as district-level systems, necessitate the use of predictive controls and AI-based algorithms. This trend suggests that more extensive systems benefit from the anticipatory and adaptive capabilities of advanced control techniques.

From this preliminary analysis, it is evident that the type of application significantly influences the selection of control methods due to the varying operational demands and complexities. Passive storage systems, which typically have lower dynamic variability, are often managed with classical control methods that do not require prediction. In contrast, active thermal and electrical storages, which have higher operational complexities and require more precise management of energy flows, benefit from predictive controls. These advanced methods can optimize performance by forecasting future states and adjusting operations accordingly.

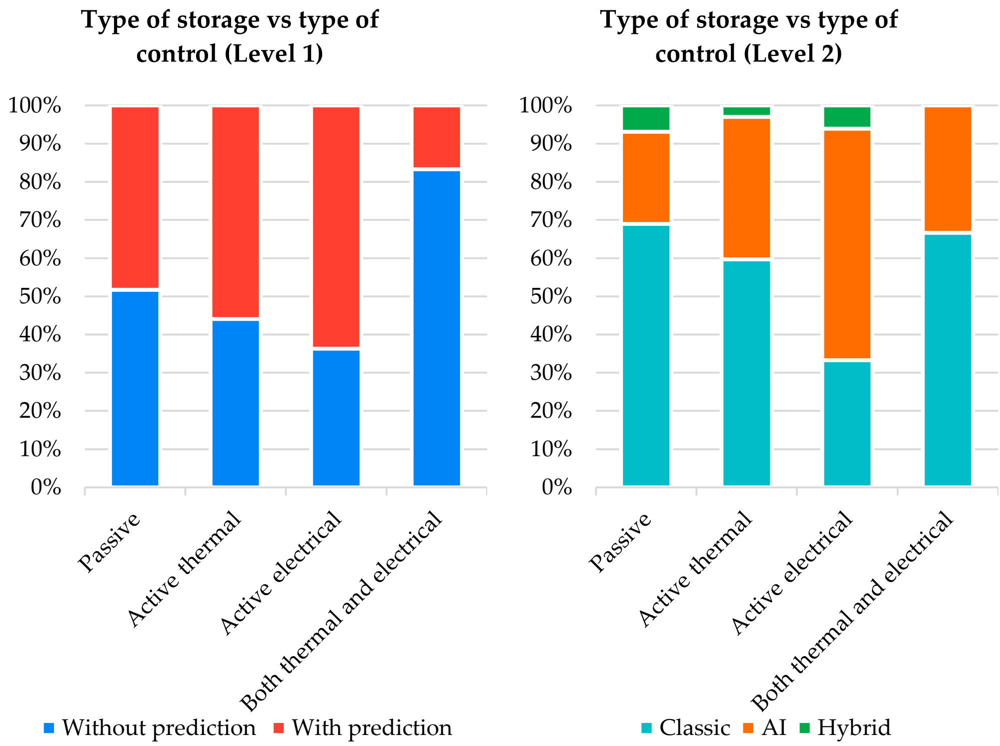

Figure 6. Relationship between the different levels of energy storage control.

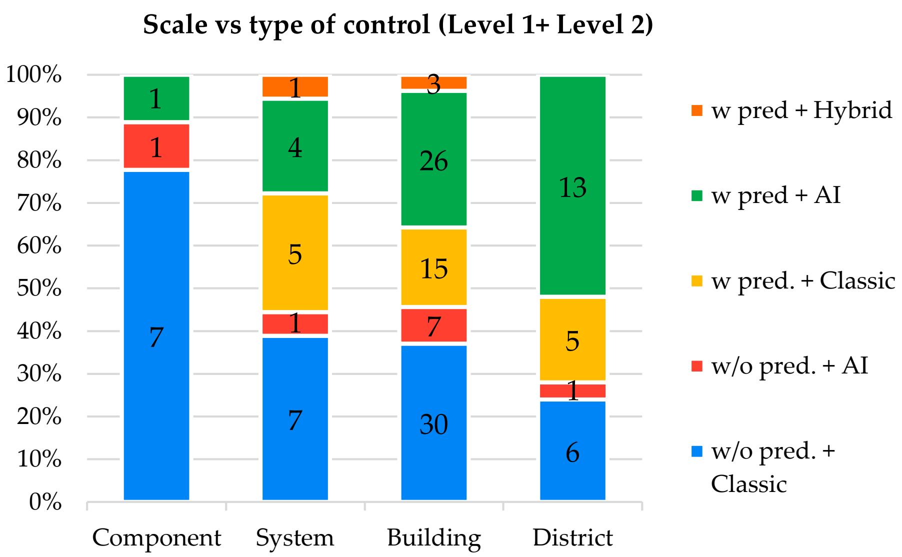

Figure 7. Relationship between the scale of the study and the storage control.

Conversely, control methods play a crucial role in facilitating both numerical and experimental applications. Classical control methods, being straightforward and well-established, are easier to implement and validate through experimental setups. They provide a reliable baseline for system performance. On the other hand, AI-based and hybrid control methods enhance numerical simulations by providing adaptive and predictive capabilities that can handle complex scenarios and uncertainties. These advanced methods enable more accurate modeling of real-world conditions and can improve the efficiency and effectiveness of experimental designs.

Overall, a general analysis of the literature suggests that the choice of control method is closely linked to the type and scale of the application. Advanced predictive and AI-based controls are preferred for more dynamic and large-scale systems, offering significant advantages in both numerical and experimental contexts. Figures 5–7 collectively demonstrate the evolving landscape of control strategies in energy storage systems, highlighting the shift toward more sophisticated and adaptive methodologies as system complexity increases.

3.3. Insights: Non-Predictive Control Strategies for Energy Storages

3.3.1. Applications without the Support of AI

Among the papers that were analyzed, 18 papers used classical control techniques without prediction. Figure 8 shows the types of classical control used in the papers. Most of the studies implemented an on/off control, and two studies implemented P, PI, or PID controls (controllers using error dynamics). Some studies with on/off control adjusted their control setpoint based on criteria such as schedules [15], predefined curves [16], or energy prices [17].

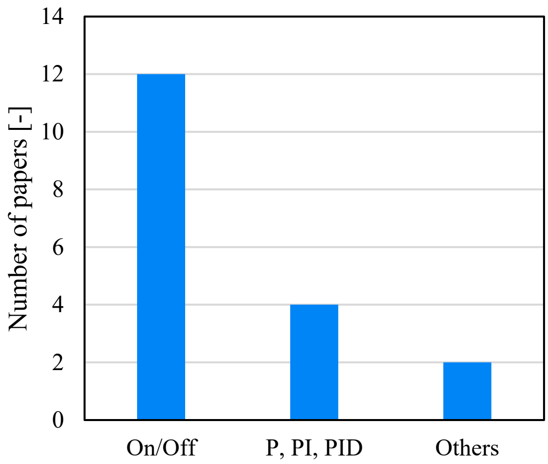

Figure 8. Non-AI-based control strategies without prediction: distribution of selected studies.

The selected studies report on the benefit of energy storage through the more efficient operation of the coupled system components, such as the reduced operating hours of the heat pump. In order to report some of the features of such applications, here are some summarized relevant studies of this approach. Meng et al. [18] conducted an experimental study of a variable air volume (VAV) air conditioning system with an air source heat pump and thermal storage tank. The heat pump was operated with an on/off control based on the return chilled water temperature. The charge/discharge of the thermal storage tank was performed at fixed times. The use of heat storage reduced the on/off times of the heat pump from 43 to 7 times a day with summer settings and from 36 to 7 times a day with winter settings, compared to scenarios without any storage. Zhang et al. [19] conducted an experimental study accompanied by a simulation of a hybrid solar/biomass heating system with a water storage tank. Water temperatures from the solar panels and storage tank were monitored to control the on/off behavior of the biomass boiler and the switching of the heat source (solar panels, storage tank, or boiler). The heat pump was operated with a step control of 0, 60, 80, and 100%, depending on the outdoor temperature. A simulation study of a residential building in Lvling, China, showed that among the 1975 h of heating hours, 749 h was operated with just the supply water from the storage tank. Qiang and Zhao [20] investigated the addition of a cold water storage tank to improve the operation of a gas engine heat pump (GEHP) system. The GEHP was connected to an office building for cooling purposes and domestic hot water supply. Three operation modes were assumed according to the cooling load: (i) Low load—energy is supplied from the energy storage when the building load decreases; (ii) Medium load—heat pump supplies energy to the building and to the energy storage; (iii) High load—heat pump and energy storage supplies energy to the building simultaneously. Adding the cold water storage tank with the current control strategy allowed the engine to run within economic mode all day, leading to a stable and efficient GEHP. The primary energy ratio improved by 68%, 9.5%, and 33% in the low, medium, and high loads, respectively, after adding the cold water storage. In 2022, Wang et al. [21] introduced a novel Coupled Air and Ground Source Heat Pump (CAGHP) system with energy storage, achieving an average COP of 2.3 in winter by utilizing auxiliary heat sources and energy storage with an optimized defrosting control strategy. Their system demonstrated a 13.9% increase in heating capacity compared to traditional methods, with a 42% reduction in operating costs and a 7.14% decrease in carbon emissions, highlighting its economic and environmental advantages over conventional Ground Source Heat Pump (GSHP) systems.

Among the selected articles in the subset without AI support, energy storage in the context of demand response (DR) was commonly studied. Some studied the DR potential of the storage by its load shifting capability, while others studied price-based demand response. Chen et al. [22] conducted an experimental study to evaluate the DR potential of the building's thermal mass and a thermal storage tank. The DR potential was evaluated by the cooling load reduction when pre-cooling or a setpoint offset was adopted in the system control. Within the conditions of the experimental setup, the pre-cooling (and hence the charging of the building thermal mass) maintained comfort conditions for over 90 min without the use of active cooling. The use of a 200 L water storage tank with 9 °C chilled water was able to meet the cooling demand for over two hours for the 32 m^2 test facility. Romaní et al. [23] conducted a simulation study with an experimentally validated numerical model of a room with a radiant wall acting as a thermal energy storage, which was coupled with a photovoltaic (PV) panel. Different control setpoints of the room for the on/off behavior of the heat pump were tested, with different priorities such as maintaining room temperature, maximizing PV energy production, and minimizing energy imported from the grid. By charging the radiant wall during off-peak hours, a maximum of 84% cost reduction compared to the baseline (on/off based on room temperature control) was achieved in the studied case. The authors identified parameters that could be further investigated, such as indoor temperature setpoint, threshold of the PV output for activating the heat pump, and the prediction of PV production, cooling load, and charging time. Cichy et al. [17] conducted a simulation case study of a large residential building with heat pumps, solar thermal collectors, hybrid collectors, PV panels, thermal storage tanks, and lithium-ion battery storages. Price-depending control was adopted to adjust the setpoint temperature of the storage tank indoors. The most efficient heat source at the time was selected to operate the heat pump. Compared to a fixed setpoint control, the price-depending control led to an overall cost reduction of 14%. Guo et al. [24] conducted a simulation study on the demand response potential of a ventilated electric heating floor system, where the thermal mass of the floor was used as storage and the ventilation was used for discharging. Heating from the floor system was controlled by a PID controller. A fixed indoor temperature setpoint control and a control that varied the indoor temperature setpoint based on the DR status were simulated. The active discharge of the floor with ventilation reduced energy use by up to 37% with a constant setpoint control and by 62% with a DR-based control. Chapaloglou et al. [25] used a model of a microgrid consisting of a sports center with a heat pump, PV modules, and a battery to study the influence of two rule-based controls, peak shaving, and price arbitrage, on the electricity cost. The peak shaving strategy made use of the stored electricity in the battery during periods with high load. In the price arbitrage, electricity could be stored in the battery during periods with electricity prices lower than the daily mean. The stored electricity could then be used in periods when the electricity prices exceeded the daily mean value. Cost reduction was obtained under both strategies, but with up to 23 percent points higher with the price arbitrage control. These values are, however, dependent on the on-site energy production from the PV modules. Coccia et al. [26] carried out a demand-side management analysis for a water loop heat pump (WLHP) system integrated with a refrigeration system for building climate control and food preservation in a supermarket. A model was developed in TRNSYS, where the role of the water loop and its thermal inertia for energy flexibility was investigated. The demand-side management analysis based on the real-time electricity price showed that the setpoints that regulate the WLHP operation, namely heat recovery set-point temperature, auxiliary heater set-point temperature, and dry cooler set-point temperature, could be updated to reduce yearly electrical energy costs. By also optimizing the storage tank volume, a similar overall energy use was obtained but with a reduction in the yearly electricity cost −4.35% (around 2000 EUR for 5411 m^2 of thermally controlled area). A particular application of an active electrical storage system was studied by Park et al. [27]. The authors propose a sensor-based monitoring and control system for managing temperature and humidity in container-type energy storage systems, demonstrating that their rule-based air conditioner control algorithm reduces average humidity by 11.4% while maintaining optimal temperature conditions.

There has also been an increasing number of studies investigating the use of phase change materials (PCM) for thermal storage. Most studies are still at the phase of developing and testing components containing PCM, and complex controls are yet to be tested. Hu et al. [28] conducted experimental and simulation studies on a newly developed, PCM-enhanced, ventilated window. The charging and discharging of the PCM was managed by changing the openings for ventilation, and the change in mode was determined by the time, season, and indoor temperature. Compared to the primitive control with no mode changes, the control proposed by the authors resulted in energy savings of up to 62% in summer and 9.4% in winter. Stathopoulos et al. [29] investigated the load shifting potential of an air-to-PCM heat exchanger. For the analysis, both experimental and simulation data were used where the heat exchanger was integrated into the mechanical ventilation system, which supplied air to a room. The implemented control stopped active heating from 18:00 to 20:00 when the peak winter daily electricity demand was found to occur in France. During off-peak hours, the PCM was charged by the incoming air, which was actively heated using electrical resistances. The stored heat was then released to the air being supplied to the room. The study showed that by integrating the PCM, 9 to 10% of the energy could be shifted to the off-peak period while managing to maintain a constant room temperature. Li et al. [30] investigated the development of a novel solar heat pump heating system, which used PCM as the heat storage. An air-type solar collector with encased PCM was used to store thermal energy. During periods with insufficient solar radiation, the energy stored in the PCM could be utilized as a heat source to the evaporator of the heat pump providing indoor heating. The control system switched operation between the following: (i) Solar heating mode; (ii) Solar-assisted heat pump heating mode; (iii) Heat pump heating mode. This depended on the indoor temperature, the solar radiation intensity, and the solar collector's internal temperature. Experimental results showed that the solar collector could continuously supply heat for 9.5 h with an average thermal efficiency of 45%. The energy stored in the PCM could power the heat pump efficiently for 3 h. A case study over a period of 30 days during the heating period in Tongliao, China, showed that the system managed to maintain the indoor temperature between 21 and 24 °C. An economic analysis showed an annual heating cost reduction of 73% when compared to an electric boiler heating system. Several studies have reported on the development of radiant ceiling panels with PCM, such as Bogatu et al. [31] and Gallardo and Berardi [32]. An early study by Bourdakis et al. [33] showed that the PCM panels could passively absorb the internal heat during the daytime and be discharged in the night time (either by ventilation or by water cooled by night sky radiative cooling). Hence, it was shown that PCM ceiling panels have a peak shifting effect similar to that of a thermally active building system. A recent study by Gallardo and Berardi [34] conducted a simulation study to evaluate the energy flexibility potential of their PCM panels. The results showed that the panels (with a ceiling coverage of 66%) yielded an average heat storage capacity of about 430 Wh/(m^2·day) and an average annual storage efficiency of 86%. Compared to the baseline all-air system, the PCM panel system was also able to shift the electric power demand by 8 h.

Despite the numerous studies that have demonstrated the advantages of energy storage, certain limitations have been identified with regard to its design and control. One of the precautions that must be taken is reducing the parasitic loss of storage by means such as insulation. Le et al. [15] conducted a simulation case study of a cascade air-to-water heat pump system to be used in a retrofit of a residential building. Three heating strategies were compared: (i) Direct mode—the heat pump provided heat directly to the house; (ii) Indirect mode—the heat was first provided to the water storage tank and then to the house; (iii) Combined mode—the tank was charged during the night and the heat pump provided heat directly to the house when the tank was discharged. The on/off behavior of the heating system was controlled by a room thermostat. In the studied scenario, the average room temperature of all three heating strategies was 19.6–19.8 °C. However, the annual electricity use was highest with the indirect mode (17,304 kWh) and lowest with the direct mode (11,777 kWh). The operating cost was highest with the indirect mode (GBP 3028) and lowest with the combined mode (GBP 1976). The annual system coefficient of performance (COP) of the indirect mode was 33% lower than the direct mode due to parasitic losses of the storage tank. Bengoetxea et al. [35] conducted an experimentally validated simulation study of a hybrid system for heating and domestic hot water production comprising a micro-CHP (combined heating and power), a condensing boiler, and a thermal storage tank. The on/off and charge/discharge behavior of the components were controlled based on the setpoint of the micro-CHP return water temperature, tank temperature, and return water temperature from the consumptions (demand-side). The corresponding setpoint temperatures were determined by an optimization function to minimize cost and to maximize exergy performance. The optimized control yielded a 7% cost reduction and 4% higher exergy efficiency compared to the baseline control from the experiments. However, the authors also pointed out that in order to benefit from the optimized control, proper insulation is necessary, which keeps the transmission loss below 5% of the energy consumed.

Contrary to the studies summarized above, classical control without any prediction did not provide adequate performance in some cases. Belmonte et al. [36] conducted a simulation study of a building equipped with a water-to-water, solar-assisted heat pump system, which was coupled with a water and phase change material (PCM) tank. The charge/discharge of the heat storage components was thermostatically controlled with a dead band. The simulation results showed that the use of the PCM tank led to worse results, i.e., 30% less useful solar energy collected, 30% less solar energy transferred to the heat pump, 6% lower collector efficiency, and the reduction of heating availability from 99% to 73%. The reduced performance was associated with the longer charging/discharging behavior of the PCM. The authors pointed out the importance of a more optimized control strategy to take full advantage of the storage capacity of the PCM tank. One method for improving a system with energy storage from a control perspective would be to refine controls of multiple components, as suggested by Borreli et al. [16]. The authors conducted a simulation study testing different control strategies for a heating system in an existing nearly zero energy building (nZEB). In the baseline control, the boiler operation was controlled to maintain a fixed setpoint inside the water storage tank. The baseline control was compared with other strategies, such as a scheduled setback of the tank temperature or a variable temperature setpoint of the tank, depending on the outdoor temperature. With the combination of a variable tank temperature setpoint and early air handling unit (AHU) operation time, primary energy use was reduced by 32–46%, and hours within the comfort range (20–24 °C) increased by 0.6–3.4% compared to baseline. The study concluded that in order to achieve energy savings and comfort, it would be necessary to optimize the control of each component within the system (i.e., AHU and boiler). Other studies have also identified the necessity for the implementation of more advanced control methods, such as model predictive control (MPC) and energy and demand forecast [37], showing that integrating MPC into energy storage systems resulted in a 15% to 30% increase in energy savings compared to traditional control methods [38].

3.3.2. Applications Supported by AI

Modern nature-inspired optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used mostly to optimize the schedule of combined cooling, heating, and power (CCHP) systems with TES at the district or building level. Among the papers selected for review in this section, it is possible to distinguish those that employ a metaheuristic approach (e.g., GA or PSO) from those that implement expert systems logic. As demonstrated by Figure 9, recent research prefers metaheuristic optimization algorithms over expert systems logic control techniques in control systems due to their flexibility, global optimization capabilities, ease of implementation, robustness, and superior performance in handling complex and dynamic environments. In recent years, the support of AI-based methodologies has, in fact, greatly facilitated the development of metaheuristic optimization systems [39].

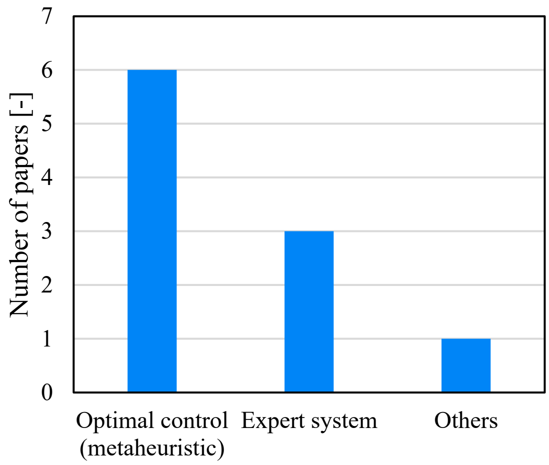

Figure 9. AI-based control strategies without prediction: distribution of selected studies.

Li et al. [40] combine GA and dynamic programming (DP) and propose an effective hybrid optimization framework to find the optimal day-ahead scheduling as well as real-time dispatching of a CCHP system with TES. They try to minimize a multi-objective cost function, including energy consumption, operation costs, and environmental impacts. Their results show that the proposed scheme increases the overall performance by 1.92% in summer and by 1.91% in winter in comparison with the conventional GA method. The authors have achieved this result, although limited, while maintaining an acceptable computational cost compared to traditional methods, a result not granted when AI-based systems are implemented.

Zhang et al. [41], in a similar work, combine GA and stochastic dynamic programming (SDP) to propose a two-stage optimization scheme for an integrated energy system (IES) with demand response (DR) and TES. (IES is just another term for referring to CCHP systems). They try to minimize multi-objective cost functions including operation costs and thermal comfort. The optimization problem is divided into two sub-problems, namely demand-side and supply-side, which are solved iteratively. GA is applied in the first stage to determine the optimal electricity, cooling, and heating demand curves considering the comfort requirements of consumers. SDP is then exploited in the second stage to find the optimal schedule for storage and energy production subject to the demand curves resulting from GA. The results of the second stage are then given back to the first stage to reoptimize the demand curves. The process loops until the optimal operation schedule and demand curves are obtained. Their results show that the proposed method reduces operation costs by 3.6% in comparison with the conventional GA method.

Wang et al. [42] apply a decentralized optimal control method based on a multi-agent system (MAS) to minimize the operation cost of CCHP systems with TES by exploiting GA. Their results reveal that the operation cost is reduced by 10.0% on a typical summer day and by 7.7% on a typical spring day compared with a rule-based control method.

Li et al. [43] use a multi-objective seagull optimization algorithm (MOSOA) to optimize the energy consumption, operation costs, and environmental impacts of CCHP systems. They propose an operation strategy called "following the state of thermal storage tank" (FST) and compare its performance with the two common strategies named "following the electric load" (FEL) and "following the thermal load" (FTL). Their results indicate that the novel proposed strategy is more economical and reduces fuel consumption effectively. It increases the primary energy saving ratio by 2.53% and 2.43% in comparison with FEL and FTL strategies.

Apart from the mentioned studies regarding the district level, Barthwal et al. [44] exploit multi-objective GA to optimize phase change material (PCM) and ice-based TES systems for air conditioning applications at the building level. The objectives include exergy efficiency and total annual cost. Inlet and outlet temperatures of the air handling unit (AHU) for the discharging cycle, storage temperature, evaporator temperature, and condenser temperature are five decision variables for the optimization program. They optimize the performance of the system in partial and full operating modes for two refrigerants. Their results reveal that the exergy efficiency of ice-based TES systems in full-mode operation is about 33% higher than in partial-mode operation. However, it is achieved by compromising the total annual cost. In addition, PCM-based TES systems demonstrate higher exergy efficiency and higher total annual cost in comparison with ice-based TES systems.

Beside the metaheuristic optimization algorithms, fuzzy logic methods are also applied to improve the performance of TES systems at residential and district levels. For example, Tascioni et al. [45] suggest a smart control strategy based on a fuzzy logic approach for a latent heat TES system in a micro-scale concentrated solar power (CSP) plant linked with a combined heat and power (CHP) unit. Their results show that the proposed strategy increases electricity produced by the CHP unit by about 5% and simultaneously reduces thermal losses in the CSP plant by 30%. A similar problem was solved by Khajeh et al. [46], demonstrating that integrating a fuzzy logic controller into a smart home energy management system with flexible appliances and a battery energy storage system can significantly enhance the provision of active and reactive power flexibility services to both transmission and distribution system operators, resulting in substantial economic benefits and improved performance compared to other models.

Gao et al. [47] utilize a fuzzy controller to dispatch and control a TES system within an IES. They propose an optimal scheduling approach consisting of two layers: one layer for day-ahead scheduling and the other one for real-time dispatching. The fuzzy logic controller is implemented in the second layer for managing the electrical and thermal storage subsystems. Their results show that the proposed method reduces the operation cost by between 1–2% in comparison with two conventional scheduling methods. With regard to the optimization applications, in 2023, Hunter-Rinderle et al. [48] propose a two-stage stochastic optimization model that improves the resilience and reliability of residential electricity supply by using on-site energy storage, demonstrating how a combination of real-world data, surveys, and occupant algorithm efficiently manage energy storage in real-time, despite the challenges of low disruption probabilities and the need for strategic energy use during outages.

AI-based control strategies have also recently been investigating broader boundaries, as in the study by Zheng et al. [49], focused on identifying cross-region electricity demand response in China, specifically focusing on integrating wind power within the national grid. The study aimed to address the challenges associated with data integration and accurate identification of EDR anomalies in the context of large-scale renewable energy participation in the electricity demand response market. Using a machine learning-based approach, the authors enhanced identification accuracy and improved the stability and management of large-scale cross-region renewable energy market.

The reviewed literature underscores the transformative potential of AI-based technologies in optimizing the control of energy storage systems across components, buildings, and districts. From smart homes to large-scale district and nation-wide systems, AI-driven approaches demonstrate remarkable capabilities in real-time monitoring, decision-making, and system optimization. The literature suggests that AI technologies hold promise for revolutionizing energy storage management. Nevertheless, further research is necessary to fully investigate the potential of AI-based control strategies and their integration with predictive controls in order to develop comprehensive energy management solutions.

3.4. Insights: Predictive Control Techniques

3.4.1. Applications without the Support of AI

Figure 10 gives a general overview of the characteristics of the models implemented to make predictions, specifying their nature, assumptions, and applications. The classic controller with prediction means that the controller schedules the control variables based on prediction from white-box models or grey-box models. It could be further classified as a classic model predictive controller (MPC) or rule-based controller (RBC) based on whether or not an optimization procedure is involved in solving the optimal control signals. As depicted in Figure 10, this review procedure found 21 existing studies on the application of such classic predictive-based controllers to buildings/systems equipped with energy storage systems. Among them, 18 papers focused on developing classical MPC, while three studies developed RBC based on the predictive result. Additionally, six studies predicted the building/system status or performance based on grey-box models, while fifteen papers developed white-box models. Moreover, most of the studies evaluated the applicability of proposed controllers based on numerical study, while only three papers applied the classic controller in a field experiment.

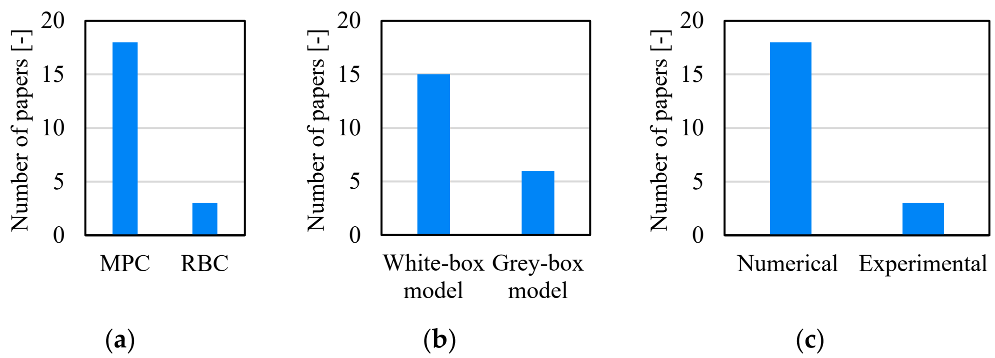

Figure 10. Paper distribution on the following: (**a**) MPC or RBC; (**b**) White-box model or grey-box model; (**c**) Numerical study or experimental study.

For most of the papers analyzed, it was possible to trace the control algorithms implemented by the predictive models back to the reference taxonomic categories, as shown in Figure 11. Most model-based predictive algorithms, when not using AI, implement on/off or PID strategies.

Existing studies on the classical MPCs usually developed a white-box/black-box model for the studied systems/buildings/district to predict their status/performance, such as energy demand and indoor air temperature. Then, the predicted values would be used to form the objective function or constraints of an optimization problem to minimize the operation cost, energy cost, or peak loads while ensuring a comfortable indoor environment and/or making sure the devices work within their rated conditions. A detailed review on classical MPC is presented below.

Salpakari and Lund [50] developed physical realistic models for a heating system that consists of a ground-source heat pump with an electric heater, a thermal energy storage system (i.e., a water tank), a battery, and a hydronic heating system. Then, they integrated these models into the electricity cost optimization function of an MPC to obtain the hourly optimal compressor power, electric heater power, battery power, mass flowrate of the hydronic heating system, and number of running shiftable appliances. Additionally, they applied an RBC to maximize PV self-consumption. Through a numerical case study on a Finnish low-energy house, the cost-optimal control resulted in 13–25% in electricity cost savings and an 8–88% decrease in the grid feed-in, compared to the inflexible reference case that did not include a battery or any shiftable appliance.

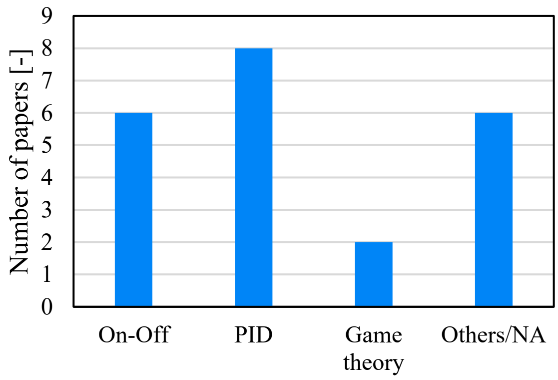

Figure 11. Non-AI-based control strategies with prediction: distribution of selected studies.

Similarly, Tang and Wang [51] predicted the power demand of chillers based on the cooling supply and coefficient of performance (COP). Meanwhile, they developed a building thermal model and simplified it as a linear discrete-time state-space model to predict the indoor air temperature. Then, an optimization problem was conducted to optimize the set point of chiller power demand and cooling discharge rate of a cooling storage system, with the aim of minimizing power consumption while ensuring an acceptable indoor environment. By adopting this MPC into a TRNSYS model of a central air-conditioning system in a commercial building, the MPC was proven to be able to achieve expected power reduction and improve the indoor thermal environment.

Descamps et al. [52] assumed perfect forecast/prediction (i.e., the predicted values are the same as actual ones) for weather, heat load, and electricity cost in the MPC that is aimed at minimizing the operational cost of a district heating network, which combines a heat pump, a gas boiler, and a solar thermal productor and a thermal storage tank. The MPC reduced the operational cost by up to 5% compared to a rule-based controller (RBC).

Moreover, one type of commonly used classical MPC is called mixed integer linear programming (MILP). For example, Martínez Ceseña and Mancarella [53] proposed an operational optimization framework based on MILP to obtain the optimal half-hourly time-ahead set points for all controllable devices (including electrical energy storage and thermal energy storage systems) in a smart district with the aim of minimizing energy cost. Fratean and Dobra [54] applied a MILP controller to control the heating/cooling system, energy generation system, and storage system, with the aim of reducing the energy consumption and lifecycle cost of two buildings in Bucharest, Romania. Furthermore, Duman et al. [55] integrated MILP into an HEMS to optimize the day-ahead operation schedule of battery energy storage systems and electric vehicles. In this study, the experimental house was simulated by a 1R1C model, while other devices (including refrigerators, electric vehicles, PV generation, air conditioners, etc.) were modeled by white-box models. They found that the smart HEMS decreased the daily cost by 53.2% under the time-of-use (TOU) tariff of Turkey by taking advantage of self-consumption.

The classical MPCs have been used when investigating the energy storage capacity and peak shifting ability of both passive and active energy storage systems. For instance, the joint electrical and thermodynamic model of buildings and low voltage networks (LVNs) in a district were simulated as a white-box model by Jazaeri et al. [56] while considering the thermal properties of four types of wall constructions. Their study found that high thermal inertia from inside enables the building to shift the entire cooling load from peak periods to off-peak periods. Azuatalam et al. [57] investigated the effect of the thickness of phase change materials (PCMs) on the heating cost of a building controlled by an RC model-based MPC that minimizes the heating cost and the difference between the desired indoor air temperature and the measured value. Wei and Calautit also conducted a recent study that focused on PCM storage [58]. The authors demonstrate that a cost-effective model predictive control (MPC) system, integrated with IoT technology and PCM wallboards, can enhance energy efficiency and reduce electricity costs by 35% in building heating systems through precise, real-time indoor temperature management and strategic energy usage shifting.

To apply the classical MPCs to control devices/buildings in a district, Ouammi [59] proposed a white-box model-based MPC to comprehensively control a smart network of residential buildings by optimally scheduling the power exchanges, charge/discharge rate of energy storage devices, the state of micro-CHP and the charging state of electric vehicles. Tang et al. [60] used the game theoretic method to minimize the electricity bill of a district by optimizing the indoor air set-point temperature and the operation of an active thermal storage system. In their study, buildings were simulated by an RC model. The result shows that the proposed game theory-based decentralized control strategy decreased the peak load by ~10%, which is over two times the individual-level control strategy.

Due to the multiple time scale nature of energy storage systems and different dimensions between buildings and districts, developing hierarchical controllers based on the structure of MPC would be an effective solution when the control target includes several energy storage systems or consumers. For instance, Touretzky and Baldea [61] proposed a hierarchical controller for thermal energy storage systems. It consists of a fast control layer for passive storage and a slow control layer for active storage. The numerical study results show that the hierarchical controller resulted in over 59% cost savings compared to the baseline. Furthermore, Ferro et al. [62] proposed a bi-level controller to minimize the electricity cost of interconnected buildings in a smart grid. In the controller, the upper decision maker provides references for power exchange with the aim of minimizing cost and power losses. Following the references, the consumers manage storage systems and devices to achieve cost saving and comfort requirements.

Except of optimizing the operation of devices in buildings/districts with thermal storage systems, classical MPCs have also been used in the design stage. For instance, Sharifi et al. [63] proposed an optimal load splitting algorithm (OLSA) to optimize the hourly load splitting between a thermally activated building system (TABS) and a secondary system over a year based on an RC model of the TABS and the building. Accordingly, the design parameters (such as supply water temperature and water flow rate) of TABS could be defined based on the optimal heat flow rate calculated by OLSA.

Furthermore, most of the existing studies investigated the applicability of MPCs based on the numerical study instead of the field experiment. Here, studies based on experiments would be summarized. Bürger et al. [64] designed a one-day experiment to successfully implement a mixed-integer nonlinear MPC with the aim of economic optimization to control the operation of a solar-driven climate system, which consists of two solar thermal collectors, a hot water storage system, a cold-water storage system, and an adsorption cooling machine. Kuboth et al. [65] compared a white-box model-based MPC with a reference PI-based standard controller by using them to control heat pumps in two test rigs, which include an air source heat pump and a hot water tank. The experimental result indicates that the economic MPC reduced the heat pump operation cost by 34.0%, through averagely increasing the heat pump coefficient of performance (COP) by 22.2% and the photovoltaic energy self-consumption by 234.8%.

Although the classical MPCs could reduce the peak loads and electricity cost substantially, improving its computation speed for solving the optimization problem should be considered. For instance, Meinrenken and Mehmani [66] pointed out that solving the optimal one-day-ahead set-point temperature for an official building and battery dispatch took around 1.5 h when using a standard computer with Intel Core i5 CPU and 8 GB memory. To reduce the computation time, several solutions could be considered, such as using a faster processor, parallel computing for different zones, or simplifying the predictive model/objective function. For example, Ostadijafari et al. [67] constructed a nonlinear economic model predictive controller (NL-EMPC), in which the predicted energy consumption was multiplied by the electricity price to form the objective function, and the predicted indoor air temperature was used to set the thermal comfort constraints. Note that the indoor air temperature prediction was predicted by a bilinear model derived from an RC network model, while the energy consumption of the HVAC system and battery storage system was formulated by the state-space equations. They then mimic the behavior of NL-EMPC by a linearized economic model predictive controller (L-EMPC) that approximates the non-linear equations by feedback linearization, constraint mapping, or piecewise linearization. The L-EMPC shows comparable cost saving ability with NL-EMPC but much faster computation speed.

Another concern for classical MPCs is that they do not always show better control performance than traditional control strategies. For example, Oliveira et al. [68] found that a simple control policy for a water heater tank could show comparable cost reduction ability as opposed to a classical MPC. Improving the accuracy and simplicity of predictive models may improve the applicability of MPCs [69].

In a recent publication, Li et al. [70] present an intriguing perspective on the relationship between the impact of forecasted electricity load errors and the utilization of MPC strategies. Their findings indicate that prediction accuracy is less critical for buildings without demand charges, while accurate predictions are vital for those with demand charges. Additionally, underestimating load has a greater impact than overestimating it, suggesting the need for tailored objective functions.

Except for the MPCs, the predictive results from classic models have also been integrated into RBCs to schedule preheating/precooling of the HVAC system to take advantage of the thermal storage capacity of thermal mass [71]. Parejo et al. [72] proposed a homeostatic control strategy to control the PV generation, energy storage, and air conditioning of a building in a micro-grid. The proposed controller includes two different parts: a predictive branch and a reactive branch. The former part is aimed at maintaining a thermally comfortable indoor environment, while the later part controls the charging state of batteries to maintain the microgrid running.

3.4.2. Applications Supported by AI

Combining model predictive control (MPC) and AI to enhance the performance of heating systems with TES at building and district levels has absorbed much attention among researchers during recent years. Usually, artificial neural networks (ANN) are exploited as the predictive model within MPC approaches and/or metaheuristic algorithms are applied to solve the optimization problem. According to the proposed taxonomy, the distribution of the selected papers shown in Figure 12 shows that the algorithms in this category are more related to machine learning.

Cox et al. [73] exploit ANN for modeling a large district cooling system with ice storage within an MPC framework. GA was linked with MPC to solve the optimization problem. Their results show that the proposed method is capable of reducing operation costs between 13% and 16% compared with a fixed schedule case.

Reynolds et al. [74] exploit ANN to predict several variables, including indoor temperature, building demand, and solar photovoltaic generation, and then use them within an MPC framework combined with GA to optimize the operation schedules of an IES system with TES. Their results show that the suggested method increases the profit by 44.88% in comparison with an RBC approach.

Finck et al. [75] exploit ANN to predict solar radiation, space heating demand, and electricity consumption of a heat pump for a building heating system, including TES, and then apply an economic MPC framework to minimize the total costs of electricity consumed by the heat pump. Set points for the temperature of the domestic hot water tank and space heating tank are considered as control variables and a direct search method is applied to solve the optimization program. Their results indicate that the suggested method reduces operation costs by around 10% in comparison with an RBC method. In addition, the proposed method improves demand flexibility significantly.

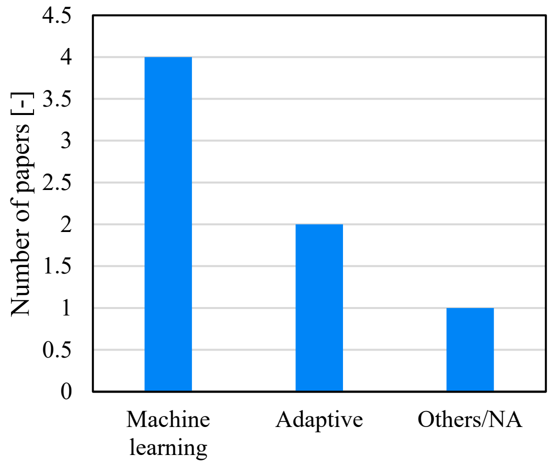

Figure 12. AI-based control strategies with prediction: distribution of selected studies.

Lee et al. [76] examine the optimal control of charging and discharging rates of a chilled water TES tank to minimize the operation cost. They use ANN as their prediction model and then apply a metaheuristic algorithm called "εDE-RJ" to solve the optimization problem. ANN models predict a few system variables, including the temperatures of the bottom, middle, and top TES tank layers. Their results show that the proposed AI-based MPC strategy reduces the operation cost by 9.1–14.6% in comparison with conventional rule-based control (RBC) approaches.

Goldsworthy et al. [77] demonstrate a cloud-based, data-driven model predictive control (MPC) algorithm for managing a 150 kWh lithium-ion battery at a commercial site. Despite hardware limitations, the algorithm achieved a 5.5% reduction in electricity costs, primarily by lowering the site's capacity charge. The study highlights the importance of real-world testing to address operational challenges such as data outages and communication issues. The flexible algorithm, though initially tested on a battery system, shows potential for broader applications, including HVAC systems and electric vehicle charging, emphasizing the need for robust, predictive control to optimize savings across complex systems.

In 2022, a study by Meng et al. [78] investigated the application of different control strategies for thermal energy storage in an air-conditioning system, demonstrating that using an Elman neural network for demand response significantly reduces energy consumption and operating costs while maintaining thermal comfort in buildings. Similarly, Xu et al. [79] illustrate the application of four different model-based deep reinforcement learning algorithms to optimally control a grid-connected residential PV-battery system in a building. The authors showed that the TD3 algorithm optimizes energy cost and self-consumption of the system, outperforming traditional baseline models.

Apart from the studies that combine MPC with AI, some papers use AI as a prediction model in combination with conventional control methods to optimize the operation of TES systems. For instance, Meng et al. utilize an Elman ANN for load forecasting as well as TES modeling. The ANN is coupled with PSO to optimize load prediction. Their results indicate that the proposed method is capable of reducing the operation costs effectively while keeping thermal comfort at a desired level.

4. Discussion: Emerging Trends and Perspectives

After conducting an in-depth review of the selected articles, it became evident that certain taxonomy categories identified in the initial classification were scarcely represented or entirely absent. Figure 13 illustrates the refined taxonomy structure presented in Figure 4, which better reflects the focus areas and prevalent methodologies within the reviewed literature. Several control strategies, particularly those categorized under non-AI-based and non-predictive methods like Game Theory, were notably underrepresented. The same happened for adaptive control methodologies in non-predictive strategies. This can be attributed to the growing trend toward advanced predictive and AI-based control methodologies in recent years, driven by their potential for higher efficiency and adaptability. As a result, the initial comprehensive taxonomy was adjusted to exclude these less prominent categories, providing a more accurate depiction of the current state of research.

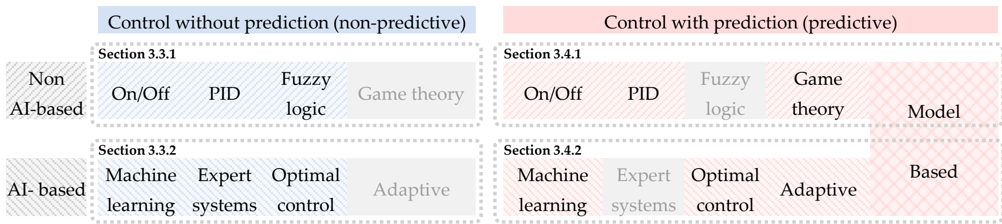

Figure 13. Taxonomy of systems and methods for energy storage: most analyzed papers included in review (gray font refers to the elements that were not found in the recent literature).

4.1. The Role of AI

Energy storage technology stabilizes the fluctuating energy supply and demand by storing and reallocating thermal and electrical energy. Environmental and economic benefits from its application are considerable, and it can be applied widely at the system, building, and district levels. However, as reported in the earlier section, the potentials and advantages of energy storage technologies are very dependent on how they are controlled.

In general, the energy storage system needs to be operated from a comprehensive perspective by considering the demand load, which is dynamic and easily influenced by external disturbances such as meteorological or building parameters [80]. In particular, the energy storage system has a strong cooperative effect with renewable energy sources, but renewable energy sources are unstable with volatility and intermittency [81].

When it comes to classical control strategies such as feedback control or rule-based control, they only focus on the current status of the external conditions and thus easily fail to lead the energy storage system to maximize environmental and/or economic profits. Therefore, to enhance the overall efficiency of the energy storage system, an advanced control strategy that considers the thermal and/or electrical behaviors of the energy storage system under dynamic operational conditions is necessary [82].

Contrary to the classical control strategies, AI-based control can help to draw up the intelligent management of the energy storage system by solving two main challenges. These are the following:

1. Prediction of key influencing factors of the energy storage system, such as energy storage performance, meteorological parameters, and demand loads;
2. Optimization to search for best solutions of control variables for the energy storage systems to consider single or multiple objectives to maximize environmental and/or economic benefits with upper and lower capacity constraints.

For instance, Rehman et al. [83] employed an AI-based control method to optimize a photovoltaic-based energy system integrated with onsite battery and electric vehicles (EV). Based on the gradient tree boosting ensemble method, profiles of the photovoltaic energy production were estimated, and the battery charging/discharging and EV charging were optimally manipulated by linear and mixed integer programming to minimize the annual cost of the purchased electricity. In their case study, the cost was reduced by 6–36% depending on the photovoltaic capacity.

In another previous research by Lee et al. [76], a metaheuristic algorithm was adopted to optimize the charging and discharging time and amount of sensible thermal energy storage system for minimizing the total operating cost. During the control phase, the usage temperature of the thermal energy storage tank and the energy consumption were predicted by artificial neural networks, and the optimization solver referred to the predicted results in the estimation of the cost function. In their experimental validation, the AI-based control method showed operation cost savings of up to 14% compared to the classic rule-based control method.

Also, Svetozarevic et al. [84] utilized a deep reinforcement learning algorithm to optimally control the EV battery system. By adopting the deep reinforcement learning algorithm in the controller, the valve opening of the water loop for the floor heating system and the charging/discharging of the EV battery were optimized to minimize the electricity cost by maintaining indoor thermal comfort. In order to determine the optimal control variables, the room temperature and the state of the EV battery were predicted by recurrent neural networks and linear models constructed based on historical data. They compared the performance of the deep reinforcement learning control policy with the classic rule-based control, and it was found that it could achieve 17% energy savings and 19% better comfort satisfaction on average.

4.2. How Storage Increases Building Flexibility and Resilience

As stated in the previous section, energy storage technology contributes to balancing energy supply and demand. This contributes to increasing the resilience of buildings and districts during disruptive and hazardous events. A report from the IPCC defines resilience as "the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner" [85]. Zhang et al. [86] further adapted this definition for evaluating building cooling strategies in the event of heatwaves and power outages and defined four characteristics for resilient cooling, i.e., absorptive, adaptive, restorative capacity, and recovery speed. This outlines the different stages of how a resilient building performs, where it would maintain design conditions under extreme events (absorptive capacity), endure at minimum desirable conditions in more extreme events (adaptive capacity), and recover quickly in the event of a failure (restorative capacity, recovery speed). Thermal energy storage technology is expected to contribute to the absorptive capacity. Active control of energy storage (both thermal and electrical) enables the system to be adaptive. The restorative capacity and recovery speed are technology-dependent.

In the event of a heatwave, thermal storage, such as building mass, can help reduce the risk of indoor overheating when coupled with discharging methods such as nighttime ventilation [87] or active water circulation [88]. Thermal storage at the source side and electrical storage can also help reduce electricity use during a heatwave when the electricity peak demands on the grid tend to increase [86], which could potentially result in a power outage. The use of predictive control with weather forecasts would enable buildings and storage systems to prepare for disruptions through efficient load management while maintaining indoor thermal conditions. When a power outage or grid failure occurs, thermal storage in the building mass will allow buildings to be habitable for a certain time before failure, especially if the thermal mass is activated (e.g., by water circulation prior to the power outage) [88]. Electrical storage will directly contribute to the resilience of buildings during a power outage or grid failure. An experimental case study conducted by Amada et al. [89] showed that a net-zero energy house with on-site photovoltaic panels and batteries was able to maintain thermal comfort in the summer of Japan with the partial operation of air conditioning units. In cases where the electrical storage is insufficient to operate active cooling systems for a building, the use of low-power personalized cooling devices (e.g., fans) may be an option to make higher indoor temperatures acceptable for the occupants [90]. Existing studies suggest energy storage-integrated systems to be a resilient solution even for areas with limited access to energy [91], but they are limited to classic, rule-based controls. Advanced control of such systems is worth investigating, e.g., predictive control in the context of heatwaves.

4.3. From Control Theory to Practice: Future Perspectives for Experimental Application

The review of current literature on control strategies for energy storage reveals a predominant reliance on simulations, while experimental studies involving prototypes or commercial products are significantly less prevalent. This discrepancy highlights a critical gap between theoretical advancements and practical implementation. While simulations provide valuable insights and a controlled environment for testing algorithms, they often fail to account for the complexities and unpredictability of real-world scenarios. Experimental studies, on the other hand, are essential for validating simulation results and understanding the practical challenges and limitations of deploying control strategies in actual systems.

To bridge this gap, several open issues need to be addressed. First, there is a need for more real-world testing of control strategies to assess their performance, reliability, and scalability under varying conditions. This includes testing with different types of energy storage systems, such as batteries and phase change materials, in diverse environmental settings. Second, the integration of Internet of Things (IoT) technologies and real-time data analytics in experimental setups can provide more accurate and dynamic control, but this requires robust and secure communication infrastructures. Third, the economic feasibility and user acceptance of these advanced control systems must be evaluated through pilot projects and field trials.

To advance toward practical applications, future research should focus on developing cost-effective and easily deployable experimental setups. Collaborations between academia, industry, and utility providers can facilitate large-scale pilot projects that not only test the technical aspects but also consider regulatory and market dynamics. Additionally, the development of standardized testing protocols and performance metrics will enable better comparison and benchmarking of different control strategies.

5. Conclusions

In the effort toward the elimination of non-renewable energy sources, energy storage technology has emerged as a crucial component in bridging the gap between fluctuating energy supply and demand. By effectively storing and reallocating thermal and electrical energy, this technology offers a promising solution to stabilize energy flows, enhance energy efficiency, and improve the resilience of buildings and districts during disruptive events.

The utilization of energy storage technology extends across various scales, from large-scale power systems to individual buildings. At the system level, energy storage can mitigate the intermittency of renewable energy sources, such as solar and wind power, enabling a seamless integration of these clean energy sources into the grid. By storing excess energy generated during periods of high production and releasing it during peak demand periods, energy storage technology can smooth out the fluctuations in energy supply, ensuring a more stable and reliable power grid.

On a smaller scale, energy storage systems can be implemented in buildings to optimize energy consumption and reduce reliance on the grid. By storing energy during off-peak hours and utilizing it during peak hours, buildings can significantly lower their electricity bills and contribute to overall grid stability. In this context, the appropriate use and careful control of storage systems in buildings is also one of the key processes for achieving concrete goals in terms of zero-energy buildings over reduced time intervals [92]. Additionally, energy storage systems can enhance the resilience of buildings during power outages, ensuring uninterrupted operation of critical systems and maintaining occupant comfort.

The advent of artificial intelligence (AI) has revolutionized the field of energy storage technology, enabling more intelligent and efficient management of energy storage systems. AI-based control systems can effectively predict key influencing factors such as energy storage performance, meteorological parameters, and demand loads. This predictive capability allows for proactive optimization of energy storage operations, maximizing environmental and economic benefits while ensuring system stability.

AI-based control also plays a crucial role in enhancing the resilience of buildings and districts during disruptive events. By analyzing weather forecasts and predicting potential disruptions, these intelligent systems can enable buildings and storage systems to adopt efficient load management strategies. During disruptions, AI can optimize energy use to maintain comfortable indoor temperatures and minimize the impact of power outages.

In conclusion, energy storage technology, coupled with AI-based control, offers a novel approach to sustainable energy management. By stabilizing energy flows, optimizing energy consumption, and enhancing resilience, this technology holds immense potential for shaping a cleaner, more sustainable, and resilient energy future.

Author Contributions: Conceptualization, M.F., A.A., F.H., R.O. and E.F.; methodology, M.F., M.B., A.A, F.H., R.O. and E.F.; software, M.F. and M.B.; formal analysis, M.F., M.B., D.-I.B., D.L., M.K., S.R., J.S., Y.S. (Ying Sun), Y.S. (Yongjun Sun) and O.B.K.; investigation, M.F., M.B., D.-I.B., D.L., M.K., S.R., J.S., Y.S. (Ying Sun), Y.S. (Yongjun Sun) and O.B.K.; data curation, M.F., M.B., D.-I.B., D.L., M.K., S.R., J.S., Y.S. (Ying Sun), Y.S. (Yongjun Sun) and O.B.K.; writing—original draft preparation, M.F., D.-I.B., D.L., M.K., S.R., J.S., Y.S. (Ying Sun), Y.S. (Yongjun Sun) and O.B.K.; writing—review and editing, M.B. and E.F.; visualization, M.F. and M.B.; project administration, A.A., F.H., R.O. and E.F.; funding acquisition, E.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.3—Call for tender No. 1561 of 11.10.2022 of Ministero dell'Università e della Ricerca (MUR); funded by the European Union—NextGenerationEU. Award Number: Project code PE00000021, Concession Decree No. 1561 of 11.10.2022 adopted by Ministero dell'Università e della Ricerca (MUR), CUP E13C22001890001, according to attachment E of Decree No. 1561/2022, Project title "Network 4 Energy Sustainable Transition—NEST, Spoke 8".

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
BITES	Building integrated Thermal Energy Storage
CCHP	combined cooling, heating, and power
EV	Electric vehicles
GA	Genetic Algorithm
HVAC	Heating, Ventilation and Air Conditioning
IPCC	Intergovernmental Panel on Climate Change
LVN	Low voltage networks
MILP	Mixed Integer Linear Programming
MPC	Model predictive control
PID	Proportional–integral–derivative
PSO	Particle Swarm Optimization
PV	Photovoltaic
RBC	Rule-Based Control
TES	Thermal Energy Storage
TOU	Time of use

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