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Review

Model Predictive Control for Smart Buildings: Applications and Innovations in Energy Management

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Abstract

The integration of advanced control strategies into building energy management systems (BEMS) is essential for achieving energy efficiency and sustaining thermal comfort. Model predictive control (MPC) has gained significant traction as a model-based approach capable of optimizing control actions by predicting future system behavior under dynamic conditions. The current review offers an in-depth analysis of MPC, combining its core theoretical foundations with a broad survey of impactful applications in buildings, for extracting key breakthroughs and trends that have defined the field over the past decade. Emphasis is placed on multiverse MPC configurations and their application across various BEMS frameworks integrating HVACs, energy storage, renewable energy, domestic hot water, electric vehicle charging, and lighting systems. A detailed evaluation of MPC key attributes is then conducted, based on essential aspects of MPC, such as algorithms, optimization solvers, baselines, performance indexes, and building types, as well as simulation tools that support system modeling and real-time validation. The study concludes by outlining key research trends and proposing future directions, with a strong emphasis on addressing real-world deployment challenges and advancing scalable, interoperable solutions on smart building ecosystems. According to the evaluation, MPC research is shifting from simple white-box setups to gray- and black-box models paired with metaheuristic or hybrid solvers, leveraging machine learning for forecasting and multi-objective optimization, but still lacking robustness, benchmarks, and real-world validation. Consequently, next-generation MPC is anticipated to evolve into adaptive, hybrid, and multi-agent frameworks that integrate forecasting and control, embed occupant behavior, enable grid-interactive flexibility, and support lightweight, explainable deployment in real building environments.

Keywords: model predictive control; building energy management; smart homes; HVAC control; energy efficiency

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1. Introduction

1.1. Motivation

Globally, buildings are responsible for nearly 34% of total energy usage and contribute approximately 37% to greenhouse gas emissions [1]. In response, in order to meet the rising demands for sustainability and indoor comfort, there is a growing interest for optimizing building energy management systems' operation, with particular emphasis on optimizing heating, ventilation, and air conditioning (HVAC) systems [2], integrating energy storage systems [3], and harnessing on-site renewable energy sources (RES) more effectively [4,5]. This trend is further enhanced by rising energy demands [6], growing expectations for indoor environmental quality [7], and increasingly stringent environmental regulatory standards [8].

Historically, energy management strategies relied heavily on static control logic or pre-defined schedules [9], often lacking responsiveness to dynamic variables such as occupancy fluctuations, internal heat gains, or external weather conditions [10]. Despite offering notable improvements, early automated systems like programmable thermostats largely operated in a reactive mode, addressing issues only after they arose [2]. More advanced practices, such as rule-based control (RBC), brought in more sophisticated logic designed by experts [9] but still struggled to manage the complexity and unpredictability of real-world building systems [11,12]. As buildings evolved into multi-system, data-rich environments, the limitations of traditional control mechanisms underscored the need for more adaptive, predictive frameworks [13]. Especially in scenarios where multiple energy systems—such as RES and storage—were integrated into the energy mix to achieve nearly zero-energy building (nZEB) standards [14], the optimization problem became significantly more computationally complex, requiring advanced algorithmic approaches like decentralized control [15]. To this end, intelligent control strategies began to gain traction, offering more dynamic, data-driven, and context-aware approaches capable of responding proactively to changing building conditions and user needs [16,17].

Intelligent approaches to building control may be broadly categorized into model-free and model-based paradigms [18,19]. Model-free techniques, such as reinforcement learning (RL), extract control policies directly from empirical data, bypassing the need for explicit system modeling [20,21]. Conversely, model-based strategies rely on mathematical model representations to anticipate system behavior and optimize control actions accordingly [22]. Within this domain, MPC stands out for its capability to forecast future states, manage competing objectives, and produce real-time control signals within a constrained optimization framework [23,24]. Unlike model-free approaches that rely solely on historical data or trial-and-error learning, MPC may anticipate future disturbances and system responses, enabling proactive and constraint-aware control [22]. Such a predictive capability not only improves performance and energy efficiency but also enhances safety and reliability—rendering MPC particularly valuable in complex, mission-critical systems like building energy management [25,26].

MPC techniques are typically distinguished by the nature of the underlying model used to emulate building dynamics, including white-box, gray-box, and black-box modeling approaches [27]. White-box MPC is grounded on first principles, leveraging thermodynamic and physical laws to construct detailed system representations [28]. Gray-box MPC integrates simplified physics-based structures with data-driven calibration for a balance between accuracy and usability [29,30]. Black-box MPC approaches, on the other hand, employ machine learning (ML) algorithms—such as artificial neural networks (ANNs) [31], support vector machines (SVMs) [32], or even RL [33]—trained on historical data to replicate system behavior without explicit physical modeling [34,35]. The selection among these modeling strategies significantly influences the predictive accuracy, interpretability, computational burden, and adaptability of the MPC solution [36].

Despite its strengths, MPC deployment in real-world BEMS applications presents substantial challenges [37,38]. Accurately modeling buildings remains difficult due to their inherently nonlinear and stochastic nature [39,40]. While white-box models demand extensive calibration and detailed data, gray- and black-box models may compromise on explainability [41]. Furthermore, solving the resulting optimization problems in real time—especially in complex or large-scale systems—may impose significant computational overhead [42,43].

Over the last decade, model predictive control (MPC) has increasingly gained recognition as a dominant framework in intelligent building control, driven by a growing body of innovative applications [44,45]. The current review aims to critically examine the recent advancements and implementations of MPC in building energy management systems (BEMS), assessing their methodologies, performance metrics, and practical outcomes. By classifying existing studies according to model type, control strategy, subsystem focus, and building typology, this work synthesizes prevailing trends and identifies research gaps. Ultimately, it seeks to inform scholars and practitioners, promoting continued innovation and effective deployment of MPC in sustainable building management.

1.2. Previous Work

The literature offers a wide range of studies applying MPC to building energy systems, with a strong emphasis on HVAC control. One notable contribution by Hilliard et al. [46] presented a systematic analysis of MPC applications in commercial buildings, demonstrating its potential to reduce energy consumption and costs while maintaining comfort. This work identified key shifts in research focus, such as the move from component-level to whole-building control, supported by a detailed case study evaluation of methods, performance, and associated challenges. More recently, Schwenzer et al. [47] provided an extensive, application-oriented review of MPC. This work delved into theoretical foundations including feasibility, stability, and robustness, and offered a classification of MPC types (linear/nonlinear, explicit/implicit). The study spanned several engineering sectors—process industries, power electronics, building systems, and manufacturing—highlighting MPC's wide-ranging applicability and emerging trends.

Similarly, Yao et al. [48] presented a comprehensive survey focused specifically on MPC strategies in HVAC systems. The review classified modeling techniques (white-box, black-box, grey-box) and discussed key design aspects such as prediction horizons, constraints, and objective functions. The study also evaluated various optimization algorithms and simulation platforms used in both real and virtual environments. Additionally, Taheri et al. [49] examined several MPC variants applied to HVAC systems, covering modeling approaches, optimization techniques, and evaluation metrics. The work emphasized technical challenges such as computational demands, uncertainty management, and real-time implementation, anticipating future research directions including the integration of deep learning, occupancy-driven control, and broader application beyond traditional building categories.

1.3. Contribution and Novelty

This review effort stands out by offering a multidisciplinary and comprehensive perspective on MPC in building energy systems, extending beyond the traditional HVAC-centric lens of earlier surveys. By including various energy systems—beyond the most prominent, such as HVACs—like energy storage, renewable integration, electric vehicle charging, and district heating, the study captures the evolving complexity and interconnectivity of modern buildings. This broader scope enables a more realistic evaluation of MPC's potential and challenges in managing buildings as holistic, grid-interactive energy hubs. Addressing this wider range reflects the increasing complexity of modern buildings and the corresponding demand for holistic, integrated control strategies.

By focusing on the most influential studies of the last decade—those with over 60 citations—the current paper evaluation ensures that insights and conclusions are shaped by high-impact research. It emphasizes the adaptability, scalability, and effectiveness of

MPC in optimizing complex integrated building energy systems. A key contribution is the structured tabular synthesis that categorizes state-of-the-art applications based on standardized criteria such as control strategy, solver architecture, system type, building and zone configuration, and deployment setting (simulation vs. real-world). This format allows a quick, comparative insight, while the citation-based analysis adds depth regarding scholarly influence.

Last but not least, unlike previous reviews, the current study undertakes a large-scale evaluation of nearly 100 significant publications—97 overall using Web of Science and Scopus Databases—from 2015 to 2025, offering a more representative view of the field. The statistical analyses derived from this dataset provide a clearer picture of prevailing trends, recurring design patterns, and underexplored areas. In doing so, the review supports both academic and industry audiences by offering a data-driven, critical assessment of MPC's current landscape in BEMS and guiding future developments. Table 1 outlines the contribution and novelty of this work in comparison to previous ones

Table 1. Contribution comparison between current and previous works on MPC for BEMS, based on key evaluation attributes.

Key Attribute	[46]	[47]	[48]	[49]	Current Work
Methodologies	x	x	x	x	x
Optimization Solvers	–	x	x	x	x
Equipment	HVAC only	x	HVAC only	x	x
Performance Metrics	–	x	x	x	x
Building Types	–	x	x	x	x
Number of Zones	–	–	–	–	x
Simulation Tools Used	–	–	x	–	x
Statistical Coverage	–	x	–	–	x
Trend and Gaps Analysis	–	–	x	x	x
Future Research Directions	–	x	x	x	x
Evaluation Depth	<30 studies	∼40 studies	∼60 studies	∼50 studies	∼100 studies

Several limitations in prior reviews underscore the need for a new, more comprehensive effort. The distinguishing contributions of the present work are outlined below:

- **Subsystem scope:** Earlier reviews were mainly HVAC-centric; this review extends to RES, ESS, EVCS, DHW, and district heating.
- **Impact basis:** Prior surveys included papers of varied influence; the present work focuses on highly cited studies (less than 60 citations).
- **Tabular synthesis:** Previous works lacked standardized classifications; here, structured tables are provided across MPC type, solver, subsystem, zones, and deployment.
- **Dataset size:** Earlier reviews analyzed 30–60 works; this effort evaluates nearly 100 influential studies from the last decade.
- **Statistical depth:** Cross-study statistics are integrated to identify trends, gaps, and recurring patterns.
- **Future outlook:** Unlike prior reviews that closed with brief remarks, this study offers structured, in-depth directions for future research.

1.4. Paper Structure

The structure of this paper may be described as follows (see Figure 1):

- ***Section 1*** presents the motivation for this review, examines prior review efforts, and highlights the unique contributions and novelty of this work.

- *Section 2* outlines the methodological approach adopted for the literature analysis, detailing the steps followed to integrate the relevant papers: article search and retrieval, filtering and selection criteria, data collection, quality assessment, and data synthesis.
- *Section 3* provides an overview of the primary building energy systems (BES) in buildings and explores the role and operation of MPC in building energy management, while also presenting common implementation challenges.
- *Section 4* presents the general mathematical structure of MPC and its types (classical, robust, stochastic, hierarchical, economic, ML-based, RL-based, etc.) and categorizes common modeling approaches (white-box, black-box, and grey-box).
- *Section 5* summarizes the influential studies published between 2015 and 2025 using a detailed tabular format, highlighting essential key attributes of each research work.
- *Section 6* evaluates the gathered works across multiple dimensions, such as: model characteristics, algorithmic MPC types, optimization solvers, baseline approaches, performance indexes, performance measures, building typology, number of zones, and simulation tools—offering comparative insights using statistical charts.
- *Section 7* summarizes the trends and gaps arising from the evaluation, compares current and previous reviews considering the generated trends, and provides future directions for MPC on BES frameworks.
- *Section 8* concludes by summarizing the key findings and contributions of the overall work.

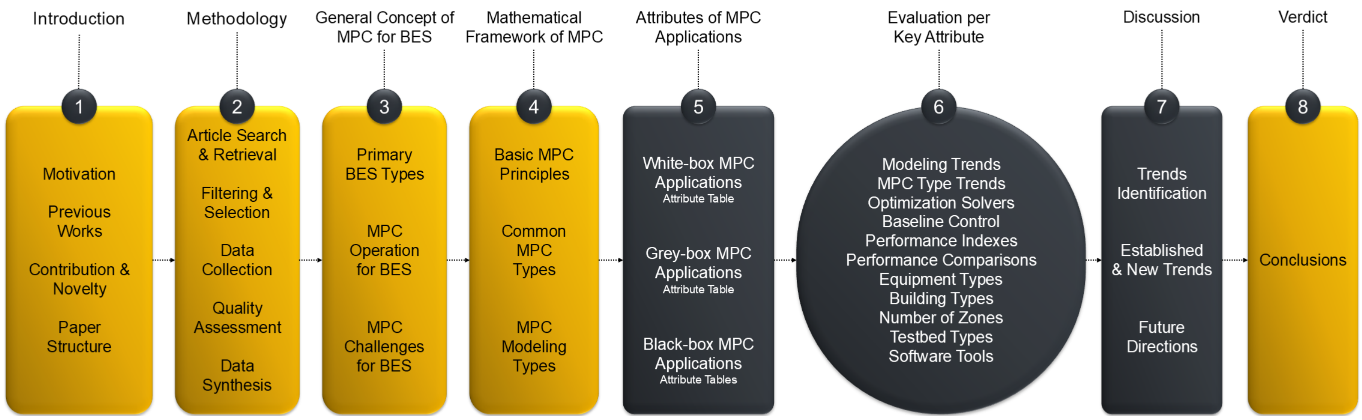

Figure 1. Paper structure.

2. Methodology

By reviewing the most impactful studies of the last decade, this paper highlights key algorithmic advances, categorizes modeling approaches (white-box, grey-box, black-box), and explores how MPC is applied across various building energy subsystems and their integrations. The analysis covers all major energy systems, such as heating ventilation and air-conditioning (HVAC), heat pumps (HPs), renewable energy systems (RES), energy storage systems (ESS), electric vehicle charging systems (EVCS), domestic hot water (DHW) systems, and lighting systems (LS). Additionally, the analysis looks into the control structures and the level of detail used in MPC models, specifically differentiating between single-zone approaches, where the entire building is treated as one combined thermal zone, and multi-zone approaches, which model multiple thermal zones separately and account for their interactions. The aim is to draw insights into the technological maturity, diversity of implementations, and practical challenges of using MPC in BEMS. The methodology followed is summarized below:

1. **Article Search and Retrieval:** A systematic search was conducted using Scopus and Web of Science (WoS). The search query combined general MPC terms with subsystem-specific keywords, for example:

   ``('Model Predictive Control'' OR 'MPC'') AND (building OR HVAC OR 'Building Energy Management'' OR BEMS OR 'Heat Pump'' OR ''thermal storage'' OR ''renewable energy'' OR RES OR ''domestic hot water'' OR DHW OR lighting OR ''energy storage'' OR ''electric vehicle charging'' OR EVCS OR 'multi-zone'')``

   Utilizing the search, an initial pool of almost 400 articles was gathered. Titles and abstracts were screened for relevance, and duplicate entries across databases were removed. Only works focusing explicitly on MPC within BEMS were retained, excluding those dealing solely with optimization, scheduling, or fault detection without predictive control relevance.
2. **Filtering and Selection Criteria:** From this initial pool, an additional screening process was applied to ensure high academic impact. Only peer-reviewed journal articles and leading conference papers with a minimum of 60 citations (excluding self-citations) were included. Furthermore, studies were required to explicitly present an MPC formulation or implementation within the building domain. This selection criteria ensured that the final dataset reflected both methodological rigor and significant influence within the field.
3. **Data Collection:** Each selected study was reviewed for its core MPC design (model type, control architecture, algorithms, optimization solvers, control horizon, objective function), targeted building subsystem, testbed characteristics (simulation vs. real-world, building type, zone layout), and performance criteria. Information on baseline comparisons, performance metrics (e.g., energy savings, comfort, cost), and whether synthetic or real data were used was also documented.
4. **Quality Assessment:** Studies were further evaluated for methodological soundness, clarity in describing the MPC framework, and depth of performance analysis. Preference was given to papers published in respected venues (Elsevier, IEEE, MDPI, Springer) and authored by experts in control systems, energy engineering, and building science. Special emphasis was placed on complete workflows, including model calibration, controller design, and benchmarking.
5. **Data Synthesis:** The findings were organized into analytical categories based on MPC type, subsystem application, control structure, and testbed setup. This structure enabled meaningful cross-comparisons and the identification of consistent trends, promising techniques, and research gaps. The synthesis aims to guide future efforts in applying MPC to smart buildings and encourage more effective implementations.

The following Figure 2 illustrates the steps mentioned above considering the literature analysis approach in a pipeline manner:

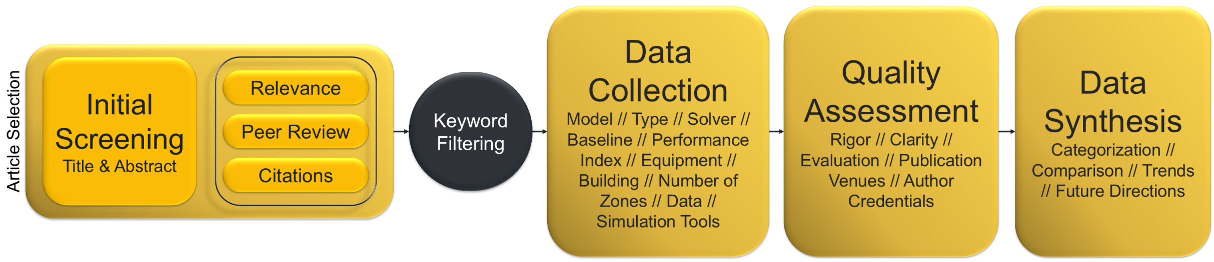

Figure 2. Literature analysis approach.

3. General Concept of MPC for Building Energy Systems

3.1. Primary BES Types

Modern buildings are equipped with an increasingly diverse mix of energy systems aimed at enhancing efficiency, flexibility, and sustainability. These include systems for thermal comfort, domestic hot water, lighting, on-site renewable generation, energy storage, electric mobility infrastructure, and more. Managing such a variety of interconnected systems requires intelligent, coordinated control. The following categories highlight the main energy subsystems typically managed in building environments [50,51]:

- **Heating, Ventilation, and Air Conditioning:** Due to their significant energy demands and complex dynamics, HVAC systems are a central focus of MPC applications. MPC enables prediction of indoor temperature trends and accordingly adjusts heating or cooling output [52,53]. In order to control HVACs sufficiently, MPC must include accurate models able to handle variable occupancy and dynamic thermal loads in real time.
- **Domestic Hot Water:** MPC helps optimize DHW systems operation by forecasting hot water demand and aligning heating schedules with cost and user availability. When integrated with thermal solar systems (TSS), MPC manages uncertainty through predictive modeling and constraints, despite sporadic usage and hybrid configurations.
- **Renewable Energy Systems:** MPC supports efficient integration of variable sources like PV and wind by forecasting generation and planning consumption or storage [54,55]. Although inherently uncertain, advanced MPC-based forecasting enhances control.
- **Energy Storage Systems:** MPC schedules battery or thermal storage charging and discharging based on predicted needs, prices, or RES inputs. Controllers need to balance system utilization with health and degradation limits, often under tight coupling constraints [56].
- **Electric Vehicle Charging Systems:** At the building level, MPC manages EV charging by predicting usage, prices, and renewable energy inputs. To this end, MPC control needs to schedule charging in order to minimize costs and grid load, while also accounting for user variability, storage dynamics, and pricing.
- **Lighting Systems:** For lighting, MPC balances energy use and comfort by anticipating occupancy and natural light availability. MPC models may incorporate forecasts for daylight and behavior patterns, requiring responsiveness to sudden environmental changes for optimal performance.

Overall, MPC offers a unified framework for forecasting behavior and optimizing control actions under system constraints. Increasingly, MPC used in managing integrated building energy systems (IBES), where multiple energy systems are centrally or distributively coordinated. Such integration requires scalable models and sophisticated control schemes capable of maintaining efficiency, system synergy, and user comfort across all devices [15].

3.2. MPC Operation for BES

The deployment of MPC within building energy systems follows a methodical, cyclic process aimed at optimizing system performance through predictive insight. Such management frameworks may integrate real-time data acquisition, state estimation, forecasting, and constrained optimization into a continuous control loop. Each stage is essential in achieving minimal energy use, sustained occupant comfort, and adherence to system constraints. The operational flow of MPC, tailored to intelligent building environments, is outlined below and also portrayed schematically in Figure 3:

1. **Data Collection:** The MPC control cycle initiates with the real-time acquisition of high-resolution data from multiple sources within the building. Such sources include indoor and outdoor environmental variables (e.g., temperature, humidity, irradiance, wind speed), as well as internal indicators like zone-level occupancy, CO_2 concentrations, and lighting levels. Subsystem energy consumption is monitored via smart meters, while operational statuses—such as battery state-of-charge (SoC), PV generation, and water tank temperatures—are logged. Exogenous inputs such as electricity tariffs, weather forecasts, and demand response signals may also be integrated, forming the data foundation for all predictive and optimization tasks.
2. **State Estimation/Modeling:** Accurate state estimation is conducted to infer unmeasurable or noisy variables, typically via observers like Kalman filters. Concurrently, models of each subsystem are employed, ranging from white-box physics-based models to grey- and black-box data-driven models (e.g., ANNs). Such models need to be adequate to capture dynamic system behavior with sufficient fidelity, while maintaining computational efficiency for real-time deployment. It is important to note that the practical implementation of MPC may vary significantly between new and existing buildings. In newly constructed buildings, sensor networks, communication systems, and supervisory controllers can be designed from the outset to accommodate MPC requirements. By contrast, applying MPC in existing buildings often involves retrofitting sensors, recalibrating equipment, and interfacing with legacy BMS infrastructure—factors that can limit both observability and controllability in real-world settings.
3. **Prediction of Future System Behavior:** Leveraging the model and estimated current state, MPC projects the system's evolution over a defined prediction horizon (from minutes to 24 h or more). This includes predictions of indoor temperatures, energy demands, and renewable production, accounting for anticipated variations in occupancy and weather. The fidelity of such predictions directly influences control accuracy and constraint satisfaction.
4. **Optimization Problem Formulation:** Based on the forecasted system trajectories, a constrained optimization problem is then formulated. The objective function is targeted to minimize cost, emissions, or discomfort, typically in a multi-objective setting. Constraints may incorporate system capacities, comfort thresholds, and temporal dependencies. This formulation enables consideration of both immediate and future impacts of control decisions.
5. **Control Decision Determination:** The optimization problem is then solved using appropriate optimization solvers (e.g., QP, MILP, NLP), generating the optimal control decisions for systems such as HVAC, ESS, lighting, and EV charging. The output comprises a sequence of control actions, designed to satisfy all constraints while optimizing objectives. Centralized or distributed MPC control architectures may be employed depending on system complexity.
6. **Control Decision Implementation:** Only the first control action from the sequence is executed—a principle known as the receding horizon strategy. This approach maintains responsiveness by allowing the system to adjust based on new data at each timestep. Control actions are communicated to building subsystems through automation interfaces and standard protocols. It should be emphasized that implementing such control strategies presents several practical challenges. While MPC is responsible for determining optimal setpoints for systems such as HVAC, energy storage, or lighting, these decisions must ultimately be carried out through physical controllers like PLCs or supervisory BMS platforms. However, many existing monitoring and automation systems do not natively support the integration of MPC algorithms. As a

result, middleware solutions or custom interfaces are often necessary to link high-level optimization outputs with low-level control execution.

7. **Update/Loop Back:** At regular intervals (e.g., every 5–15 min), the control cycle is repeated. Updated sensor data and forecasts are acquired in order to re-estimate the system state, and the optimization process is recalibrated. This continuous feedback loop ensures adaptive and resilient control, capable of managing dynamic building conditions and operational variability.

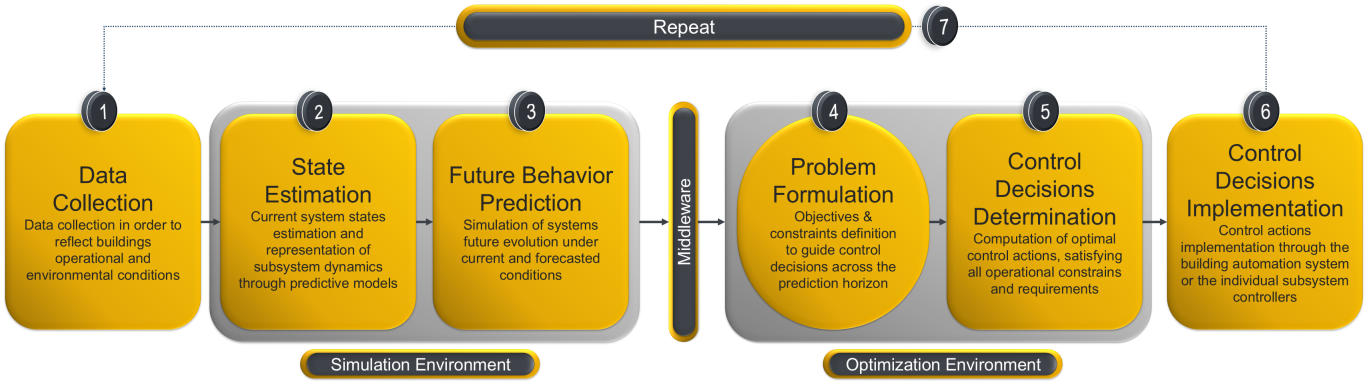

Figure 3. MPC optimization process for BES operation.

Note: The six-step description presented in this subsection is intended to provide a general framework for how MPC operates. It outlines the conceptual flow of information and decision making; however, it should be noted that this process is not universally applicable without adjustments. In practice, successful implementation depends on the specific characteristics of the building, the existing infrastructure, and the level of monitoring available.

Each of the aforementioned MPC steps is executed within a digital control infrastructure, leveraging advanced simulation and optimization software. Real-time data are processed by computational models hosted in building management systems (BMS) or cloud-based platforms. Optimization problems are defined and solved using specialized software environments (e.g., MATLAB, Python, Modelica) integrated with solvers like Gurobi, CPLEX, or IPOPT. Simulation tools such as EnergyPlus or Modelica enable high-fidelity forecasting and validation, ensuring that each stage—from data intake to control implementation—runs efficiently and adaptively within a computerized loop. The integration of optimization and simulation environments is critical for the robust design and validation of MPC strategies for BEMS. As illustrated in Figure 3, such environments interact in the closed-loop configuration, where simulators provide dynamic feedback used to refine control actions iteratively. The core components of this architecture are:

- **Optimization Tools:** These tools serve as the decision-making core of MPC. They define system models—either physics-based or surrogate—and formulate cost functions that balance energy use, comfort, and emissions. Using solvers (e.g., MILP, QP, NLP), they compute optimal strategies (e.g., setpoints, scheduling actions), which are deployed via middleware. Typical optimization tools include MATLAB and Python environments and toolboxes.
- **Middleware:** Middleware platforms (e.g., BCVTB, LabView) bridge the optimization and simulation layers, enabling seamless data exchange and co-simulation. Such middleware tools are crucial for testing and validating MPC in cyber-physical settings, particularly under disturbances like occupancy shifts or weather fluctuations.
- **Simulation Tools:** Simulators are able to emulate the physical response of building systems (e.g., thermal dynamics, energy storage, renewable generation) to applied

control commands. Such tools are able to generate output data such as zone temperatures or SoC, which feed into the next control cycle. Typical simulation tools found in the literature include EnergyPlus, Modelica, Simulink, TRNSYS, GAMS, etc.

This review provides a detailed account of the simulation and optimization tools used in the literature, presented in Section 6 under the ***Section 6.11 Software Tools.*** Readers will find an extensive mapping of tools and architectures, categorized by their function (e.g., forecasting, control), integration method, and usage frequency, offering a clear overview of current best practices in MPC-based BEMS development.

3.3. MPC Challenges for BES

While MPC provides a robust approach for building energy control, each subsystem introduces unique challenges [40]. For instance, the behavior of HVAC systems is usually highly dynamic and nonlinear, responding constantly to occupancy and weather fluctuations—a fact that complicates accurate prediction and control [57]. Moreover, integrating RES in the energy mix adds complexity with their weather-dependent outputs, complicating the limits of forecasting and requiring resilient, adaptive control strategies. When RES is integrated with ESS frameworks, efficient management requires strategic decisions on when to store or release energy, considering electricity prices, demand, and battery health [43]. EVCS further promotes uncertainty, requiring control systems to adapt to varying user schedules while aligning with grid constraints and RES input [40,58]. Moreover, energy systems such as DHW systems introduce unpredictable, user-driven patterns that demand flexible, adaptive scheduling [43]. Lighting systems, on the other hand, operate on shorter timescales, requiring rapid adjustments to occupancy and daylight changes to ensure efficiency and comfort. Figure 4 illustrates the central problem of MPC for every energy system, as well for their integrated frameworks:

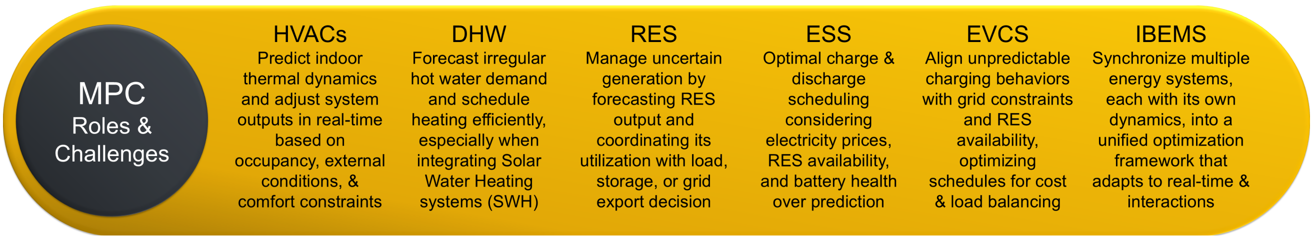

Figure 4. Challenges of MPC for BES.

At a system-wide level, managing diverse energy subsystems in a unified/integrated framework—such as IBES—illustrates a complex optimization task. It requires reconciling competing goals, coordinating interlinked dynamics, ensuring real-time responsiveness, and addressing long-term operational targets. Beyond modeling each component, the real challenge lies in synchronizing them under shared constraints and resource limitations [15]. This forms a high-dimensional, multi-scale problem where only advanced, predictive control strategies are sufficient to ensure consistent performance across the building's energy ecosystem.

4. Mathematical Framework of MPC

Mathematically, the target of MPC concerns the minimization of a cost function—often related to energy use, operating cost, or thermal discomfort—subject to dynamic models and operational constraints over a finite prediction horizon [59]. MPC frameworks facilitate multivariable control by explicitly incorporating system dynamics, bounds on inputs/outputs, and anticipated disturbances such as occupancy fluctuations, weather variations, or time-varying tariffs [60]. Unlike conventional control schemes, which typically lack predictive capability and constraint handling, MPC offers a principled approach to balancing trade-offs through optimization theory and dynamically adapting to environmental and operational changes [61].

4.1. Basic MPC Principles

MPC operates by repeatedly solving an optimization problem that predicts system behavior over a defined future horizon. This process is governed by two key parameters: the prediction horizon (N_p) and the control horizon (N_c). The prediction horizon represents the number of future time steps over which system dynamics and external disturbances are forecasted. The control horizon, on the other hand, defines how many of these steps are actively optimized using independent control inputs. In most cases, $N_c \leq N_p$, as control inputs are typically held constant beyond the control horizon.

MPC follows the receding horizon principle: at each sampling interval, updated forecasts of disturbances—such as weather conditions, occupancy levels, or energy prices—are combined with the building's internal model to solve an optimization problem. Only the first control action from the resulting sequence is applied, after which the horizon is shifted forward, new measurements are taken, and the process is repeated.

The goal of the optimization is usually to minimize an objective function that considers energy use, operating cost, and deviations from comfort conditions, while also respecting system dynamics and operational constraints. A generic formulation may be expressed as [61]:

$$\begin{aligned} \min_{u(0),\ldots,u(N_c-1)} \quad & \sum_{k=0}^{N_p-1} \ell(x(k),u(k)) \\ \text{s.t.} \quad & x(k+1) = f(x(k),u(k),d(k)), \\ & g(x(k),u(k)) \leq 0, \end{aligned} \tag{1}$$

where:

- $x(k)$ represents the system state vector at discrete time step k, e.g., indoor zone temperatures or state of charge of storage units.
- $u(k)$ denotes the control input vector at step k, such as HVAC setpoints, charging/discharging rates, or lighting control signals.
- $d(k)$ refers to exogenous disturbances, including outdoor temperature, solar irradiance, occupancy, or energy prices.
- $\ell(x(k),u(k))$ is the stage cost function, penalizing energy use, cost, or comfort deviations at each step.
- $g(x(k),u(k)) \leq 0$ are the operational and physical constraints of the system (e.g., comfort bounds, actuator limits, power balance).
- $f(\cdot)$ is the state transition model that predicts the next state $x(k+1)$ given the current state $x(k)$, control input $u(k)$, and disturbance $d(k)$.
- k denotes the discrete time index, while t (when used) refers to the absolute physical time. Thus, $x(k)$ is the state at step k, and $x(k+1)$ is the state at the next step in the horizon.

This formulation illustrates that MPC optimizes a sequence of control actions over the prediction horizon N_p, but only the first control input is applied before the horizon is shifted forward and the optimization repeated.

4.2. MPC Types

Building on these principles, MPC formulations may be categorized according to modeling assumptions, robustness, treatment of uncertainty, or computational structure. In practice, the system states $\mathbf{x}_k$ represent physical quantities such as room temperatures, storage levels, or indoor air quality indicators, while the control inputs $\mathbf{u}_k$ include HVAC setpoints, lighting commands, or energy dispatch signals. In the literature, different MPC types address distinct challenges: *classical MPC* assumes a deterministic model and forecasts, *robust MPC* enforces feasibility under bounded disturbances, *stochastic MPC* incorporates probabilistic forecasts, and *economic MPC* directly optimizes energy cost or market participation. More recent *ML-based* MPC schemes employ data-driven models to cope with modeling errors and system complexity. The following subsections provide a detailed overview of such MPC types as applied to BEMS:

4.2.1. Classical MPC

Classical MPC provides a robust yet computationally efficient control approach, especially when linear models and quadratic objectives are employed [62]. Classical MPC assumes a deterministic system with perfect modeling and forecasting, which may limit its robustness in dynamic building conditions. The system dynamics may be modeled as:

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + B\mathbf{u}_k \tag{2}$$

with a standard quadratic cost function:

$$\ell(\mathbf{x}_k, \mathbf{u}_k) = |\mathbf{x}k - \mathbf{x}\text{ref}|_Q^2 + |\mathbf{u}_k|_R^2 \tag{3}$$

Such a formulation is frequently applied in BEMS for HVAC control and other energy systems, offering ease of implementation and strong theoretical guarantees.

4.2.2. Robust MPC

Robust MPC extends the classical approach by accounting for bounded uncertainties—such as modeling errors or exogenous disturbances—within a worst-case framework [63–65]. Robust MPC ensures constraint satisfaction for all admissible disturbances $\mathbf{w}_k \in \mathcal{W}$, providing safety and reliability in uncertain environments:

$$\mathbf{x}k + 1 = f(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k), \quad \forall \mathbf{w}_k \in \mathcal{W} \tag{4}$$

It should be noted, however, that robust MPC's conservative nature and computational overhead often pose limitations, particularly for comfort-driven control in complex buildings [66]. As a result, its application in research is often prohibited in comparison to the classical MPC type.

4.2.3. Stochastic MPC

Stochastic MPC incorporates uncertainty as probabilistic distributions, allowing for more flexible decision making under forecast variability [67,68]. It replaces hard constraints with chance constraints as follows:

$$\mathbb{P}(\mathbf{x}_k \in \mathcal{X}) \geq 1 - \epsilon \tag{5}$$

and minimizes the expected value of the objective:

$$\min \mathbb{E}\left[\sum \ell(\mathbf{x}_k, \mathbf{u}_k)\right] \tag{6}$$

This MPC type enables more aggressive energy savings in applications with reliable probabilistic forecasts, although it significantly increases computational requirements [69,70].

4.2.4. Hierarchical MPC

Hierarchical MPC structures control into multiple levels—typically strategic (planning) and operational (actuation)—to improve scalability and manage complexity in large-scale or multi-zone building models [71,72]. Optimization at each level adheres to coupling constraints:

$$\text{Level } i : \min_{\mathbf{u}^i} \sum_{k=0}^{N} \ell^i(\mathbf{x}_k^i, \mathbf{u}_k^i) \quad \text{s.t. coupling with level } i-1 \tag{7}$$

Although this architecture promotes modularity, coordination challenges and potential suboptimality remain significant issues.

4.2.5. Economic MPC

Economic MPC departs from traditional set-point tracking by directly minimizing cost-related objectives, such as electricity bills or carbon emissions [73,74]. It typically solves a non-convex optimization problem expressed as:

$$\min \sum_{k=0}^{N-1} c_k \cdot P_k + \text{penalty}(\text{discomfort}) \tag{8}$$

where c_k denotes the electricity price, and P_k the power consumption. While the economic MPC type aligns closely with smart grid objectives, it requires accurate pricing forecasts and careful constraint handling to prevent comfort degradation [43,75].

4.2.6. Hierarchical MPC

Hierarchical MPC structures the optimization process into multiple layers, typically separating long-term planning from short-term operational decisions [76,77]. At the upper (strategic) level, MPC addresses slower system dynamics and broader objectives such as energy scheduling, participation in demand response programs, or day-ahead market optimization. In contrast, the lower (operational) level handles faster dynamics by refining these plans in real time—adjusting HVAC setpoints, managing thermal storage, or controlling lighting systems.

Mathematically, each control layer i solves a coupled optimization problem:

$$\min_{\mathbf{u}^i} \sum_{k=0}^{N} \ell^i(\mathbf{x}_k^i, \mathbf{u}_k^i) \quad \text{s.t. coupling constraints with level } i-1, \tag{9}$$

where $\ell^i(\cdot)$ represents the stage cost at level i, and $\mathbf{u}_k^i$ denotes the control inputs coordinated across levels. Higher levels provide reference values or setpoints, while lower levels ensure feasibility and comfort at finer time resolutions.

This hierarchical structure enhances scalability and modularity, making it particularly suitable for large-scale or multi-zone buildings, as well as integrated energy systems involving HVAC, RES, and ESS. Nonetheless, coordinating different layers remains a key challenge. Inadequate information exchange between levels may lead to suboptimal performance, and the increased computational complexity can hinder real-time implementation [78]. Despite these challenges, hierarchical MPC has gained traction in BEMS applications that require both system-wide coordination and local adaptability, offering a practical compromise between centralized and fully distributed MPC architectures.

4.2.7. ML-Based MPC

Machine-learning-based MPC employs data-driven models—typically as ANNs or Gaussian processes—in order to approximate building dynamics, particularly when physical modeling is infeasible [79]. The dynamics may be modeled as follows:

$$\mathbf{x}k + 1 = f\mathrm{ML}(\mathbf{x}_k, \mathbf{u}_k) \tag{10}$$

While ML models offer improved flexibility, they pose challenges in terms of interpretability, data requirements, and the enforcement of physical constraints [80]. However, their application in the literature has continuously gained significant attraction since physical modeling is a cumbersome and tedious task for researchers and engineers [50].

4.2.8. RL-Based MPC

Last but not least, a specific type of ML-based MPC, the RL-based MPC, leverages interaction with the environment in order to learn optimal policies over time, often modeled as a Markov decision process (MDP):

$$\pi^*(\mathbf{x}) = \arg\max_{\pi} \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r(\mathbf{x}_k, \mathbf{u}_k)\right] \tag{11}$$

Here, π portrays the control policy, γ the discount factor, and r the reward function [81]. Although this MPC type exhibits significant advantages for highly adaptive control, it requires extensive training data, simulation environments, and risk mitigation strategies for deployment in real buildings.

In summary, the versatility of MPC—spanning classical to learning-based methods—positions it as a cornerstone in the development of intelligent and efficient building energy systems. Each formulation brings unique strengths and limitations, demanding careful selection based on system complexity, data availability, and performance objectives.

4.3. MPC Modeling Types

Within the domain of MPC for BES, the classification of into white-box, gray-box, and black-box MPC modeling types serves as a foundational framework for guiding control strategy selection, implementation complexity, and generalizability [27]. Such MPC modeling types reflect the source and nature of the knowledge used to describe system behavior—ranging from purely physics-based representations (white-box) to fully data-driven formulations (black-box), with gray-box models combining both approaches. However, it should be underlined that this taxonomy is not rigid. In advanced BEMS applications, the boundaries often blur, as seen in hybrid techniques like physics-informed ANNs or surrogate models used in co-simulation environments. The choice of model type inherently influences the preferred MPC formulation: white-box models are typically used in classical or robust MPC, while black-box models are common in ML- or RL-based variants. To this end, trade-offs between modeling effort, transparency, computational feasibility, and adaptability to diverse building contexts must be carefully considered. The following Figure 5 illustrates the characteristics of the different MPC types, along with their typical alignment to white-, gray-, and black-box modeling approaches.

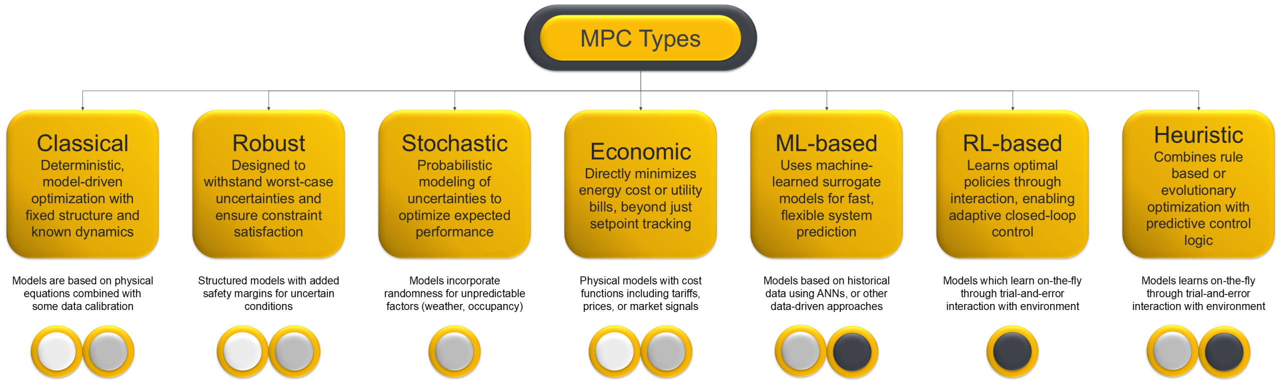

Figure 5. MPC types: basic characteristics and white-, gray-, and black-box model tendencies.

4.3.1. White-Box MPC

White-box MPC represents the most physically grounded approach to system modeling. It is derived from fundamental principles such as heat transfer laws, thermodynamics, and fluid dynamics [82]. Commonly implemented using RC network representations (simplified models of physical systems using resistors (R) and capacitors (C) to represent thermal or electrical properties) or dynamic simulation platforms like EnergyPlus or Modelica, white-box MPC ensures high interpretability and strict physical consistency. Such attributes renders white-box MPC particularly suitable for critical environments, where hard constraint satisfaction is necessary [83]—e.g., laboratories. White-box MPC is often employed in classical, robust, or supervisory hierarchical MPC frameworks. However, the development of white-box control demands significant effort, including detailed knowledge of building geometry, materials, and system components. Additionally, white-box MPC is less adaptable to changes in usage patterns, occupant behavior, or system aging, which is reasonable but limits their practicality in retrofit or legacy settings [84].

4.3.2. Gray-Box MPC

Gray-box MPC approaches bridge the gap between physics-based rigor and data-driven adaptability. This type of MPC employs low-order physical structures, where parameters (e.g., thermal resistance, capacitance, HVAC efficiencies) are identified using real data through methods like Kalman filtering or recursive estimation [85,86]. This hybrid nature retains partial interpretability while enhancing model flexibility across building types [86]. Gray-box models are especially effective in economic and stochastic MPC applications, and mid-scale hierarchical control schemes [87]. The primary advantage of gray-box MPC lies in achieving adequate control accuracy while reducing modeling effort and enabling on-the-fly updates. To this end, gray box practices seem particularly well-suited for retrofitted commercial buildings with partial documentation or limited knowledge of the system [87].

4.3.3. Black-Box MPC

Black-box MPC, on the other hand, relies heavily on data to infer system dynamics, with no embedded physical knowledge. This MPC approach is constructed using ML techniques such as ANNs (FNNs, LSTMs), Gaussian processes, or ensemble trees [88,89]. The primary strength of black-box MPC concerns the ability to capture complex, nonlinear relationships in systems with intricate actuator interactions, such as storage-integrated HVAC or EV charging scenarios [88]. Black-box MPC forms the backbone of ML-based and RL-based MPC approaches, as well as simulation-based heuristic controllers using metaheuristics like GA [90] or PSO [91]. However, the lack of interpretability, high data requirements, and difficulty in enforcing hard constraints pose significant challenges to safe deployment. Ensuring reliability often requires hybrid designs with safety constraints or fallback logic [92].

5. Attributes of MPC Applications

To efficiently present the key attributes of each MPC study identified in the literature, this paper organizes the main characteristics/attributes of each approach into structured tables. The columns of these tables (Tables 2, 4 and 6) represent significant key attributes, defined as follows:

- **Ref.**, the first column, illustrates the reference of the application;
- **Year** illustrates the publication year of each research application;
- **Type** illustrates the specific MPC type (algorithmic methodology) applied in each work;
- **Solver** illustrates the optimization solver of the concerned MPC application—e.g., nonlinear programming (NLP), linear programming (LP), quadratic programming (QP), mixed-integer linear programming (MILP), mixed-integer quadratic programming (MIQP), mixed-integer nonlinear programming (MINLP), sequential quadratic programming (SQP);
- **FH/TS** illustrates the forecast horizon (FH) and the timestep (TS) timeframes for MPC;
- **Baseline** illustrates the baseline control that acts as a comparison and validation mean against the proposed MPC approach—e.g., RBC, MPC, fixed, proportional-integral-derivative (PID) control, support vector machines (SVM), random forest (RF), etc.
- **Equipment** illustrates the energy system equipment within the controlled BEMS framework (e.g., HVACs, RES, ESS, TSS, DHW, EVs, HP, etc.);
- **Building** illustrates the building typology in which the proposed MPC took place (e.g., residence, offices, university buildings, laboratories, mixed-use buildings, other commercial buildings, etc.)
- **Data** indicates whether the data utilized to construct the MPC model are obtained from actual measurements (Real) or generated/synthesized through a simulated environments (Synth)
- **Testbed** indicates whether the building testbed generated its results in real life (Real) or generated results using a simulation environment (Sim);
- **Sim Tools** indicates the simulation tools employed, as specified in each study;
- **Cit.**, the last column, represents the number of citations, according to Scopus, of each work.

The abbreviations "-" and "N/A" represent the "not identified" elements in the tables and figures. Please note that a brief summary for each application has been integrated in the Tables 3, 5 and 7 (for white-, gray-, and black-box MPC applications, respectively).

- **Author:** illustrating the author and the reference of each application in the first column;
- **Summary:** illustrating a brief summarization of the approach and the main outcomes of the particular application.

Each application appears in the same order and with the same reference number as in the corresponding key attribute tables, allowing the reader to easily cross-reference.

Table 2. Key attributes of white-box MPC applications for BEMS.

Ref.	Year	Type	Solver	FH/TS	Baseline	Equipment	Building	Zone	Data	Testbed	Sim Tools	Cit.
[93]	2015	Classical	NLP	24 h/1 h	Fixed	HVAC/RES/ESS	Facility	20	Real	Sim	TRNSYS	164
[94]	2015	Classical	SLP	58 h/15 m	RBC	HVAC/Lights	Office	20	Real	Real	EnergyPlus	308
[95]	2015	Classical	NLP	24 h/1 h	RBC/MPC	HVAC	Office	3	Real	Sim	N/A	119
[96]	2015	Classical	N/A	15 m/15 m	RBC	HVAC	Office	8	Real	Real	EnergyPlus	89
[97]	2015	Classical	NLP	-/10 m	RBC	HVAC	University	1	Real	Real	N/A	103
[98]	2015	Classical	NLP	4 h/15 m	RBC	HVAC/RES/ESS/EV	University	1	Real	Sim	LINGO	126
[99]	2016	Classical	MILP	24 h/15 m	Fixed	HVAC/RES/ESS	Resident	1	Synth	Sim	GAMS	91
[100]	2016	Classical	LQT	-/1 m	Fixed	HVAC	Resident	5	Synth	Sim	N/A	86
[101]	2017	Classical	QP	6 h/30 m	RBC	HP/RES/ESS/Grid	Office	27	Real	Sim	GAMS	113
[102]	2017	Classical	QP	10 h/15 m	RBC	HVAC	Resident	6	Synth	Sim	Modelica	82
[103]	2017	Classical	Heuristic	24 h/10 m	Fixed	HVAC	Mosque	1	Real	Real	EnergyPlus	144
[104]	2018	Classical	MILP	5 d/30 m	Fixed	HP/RES/TSS	Resident	1	Real	Sim	GAMS	76
[105]	2018	Classical	MILP	24 h/10 m	RBC	HVAC	Resident	1	Real	Sim	N/A	74
[106]	2019	Economic	MILP	12 h/30 m	Fixed	HVAC	Resident	1	Synth	Sim	TRNSYS	123
[107]	2019	Economic	SDPT3	24 h/ 1h	RBC/MPC	HVAC/RES/ESS	Office	1	Real	Sim	GridLAB	64
[108]	2019	Classical	MILP	1–24 h/1 h	RBC	HVAC/HP/TSS	Resident	1	Synth	Sim	N/A	73
[109]	2020	Classical	MILP	24–96 h/1 h	-	HP/RES/ESS	Resident	1	Synth	Sim	EnergyPlus	64
[110]	2020	Classical	QP/NLP	24 h/15 m	RBC	HVAC/HP	Office	12	Real	Real	Modelica	87
[111]	2018	Classical	PSO	24 h/5 m	RBC	HP/RES/ESS/TSS	Resident	1	Real	Both	Simulink	98
[112]	2021	Classical	MILP	36 h/1 h	RBC/Fixed	HVAC/HP/RES/TSS	Mixed	17	Real	Sim	Python	77
[113]	2021	Classical	SCIP	N/A	RBC	HVAC/RES/ESS	Office	1	Real	Sim	EnergyPlus	71
[114]	2021	Classical	MILP	10 h/15 m	Fixed	HVAC/HP/RES	Resident	4	Real	Sim	N/A	73
[115]	2022	Classical	NLP	12 h/1 h	RBC/P	DH	University	1	Real	Sim	Modelica	62
[116]	2022	Classical	NLP	5 h/15 m	Fixed	HVAC/HP/RES/ESS	University	1	Real	Sim	N/A	60

Table 3. Summaries of white-box MPC applications for BEMS.

Author	Summary
Zhao et al. [93]	A classical white-box MPC was developed for a low-energy building with TES under dynamic pricing. Simulated using TRNSYS-MATLAB, it yielded 29% cost, 48% CO_2, and 23% energy savings using real data from Hong Kong's Zero Carbon Building.
Sturzenegger et al. [94]	A bilinear white-box MPC with Kalman filters controlled TABS, AHU, and blinds in a Swiss office. It achieved 17% energy savings and 21.6 MWh annual NRPE reduction versus RBC using CPLEX optimization and EnergyPlus-derived models.
Razmara et al. [95]	An exergy-based NMPC using YALMIP targeted GSHP-HVAC in a multi-zone testbed. It minimized thermodynamic irreversibilities, achieving 36% energy and 22% exergy savings over RBC and outperforming energy-based MPC.
Kwak et al. [96]	A real-time MPC integrated EnergyPlus and BCVTB with real EMCS data for AHU control. It saved 0.5% daily energy on peak days without an optimization solver, achieving MBE of −0.7% and Cv(RMSE) of 19.1%.
Goyal et al. [97]	In a real office zone, both a white-box MPC and a simpler occupancy-based rule controller were tested. Each saved 40% energy, showing that even simple feedback controllers offer strong performance with real-time occupancy data.
Bracco et al. [98]	A centralized MPC was developed for a smart polygeneration microgrid using LINGO NLP. Real campus data showed 15% cost and 8% CO_2 savings while coordinating tri-generation, batteries, TES, and EVs.
Sharma et al. [99]	A MILP-based MPC in GAMS optimized an islanded microgrid's energy dispatch using PV, ESS, HVAC, and diesel generator. Simulations showed 17% cost and 8% energy reductions, and halved ESS charging cycles.
Salakij et al. [100]	This MPC integrated a reduced hygrothermal model (Re-BEAM) into a linear quadratic tracker to optimize residential HVAC. Using synthetic weather data, it cut energy use by 42.6% and lowered thermal peak loads.
Razmara et al. [101]	An MPC coordinated B2G systems (HVAC, PV, ESS) to reduce cost and offer grid services. Real testbed data confirmed 29% cost and 67% ramp-rate reduction using QP optimization with YALMIP.
Picard et al. [102]	This study explored how ROM complexity impacts MPC performance in climate control. Offset-free MPC compensated model mismatch and showed that using high-order models did not increase CPU time significantly.
Aftab et al. [103]	Using video-based occupancy tracking and EnergyPlus co-simulation, this MPC achieved 23–39% energy savings in a mosque. Results were experimentally validated using Raspberry Pi hardware and real weather data.
Weeratunge et al. [104]	MILP-based MPC controlled a SAGSHP system in a residential setting with PV, electric heater, and storage. Under dynamic pricing, 7.8% cost savings were observed using real solar and load data.
Baniasadi et al. [105]	A dual-MPC system controlled GSHP and FCUs with real-time pricing using MILP. Experiments in a smart lab achieved an 85% peak load cut and >25% energy cost savings over thermostatic control.
Hu et al. [106]	The study proposed an economic MPC for floor heating in residents under dynamic electricity pricing. A stochastic RC model was developed and integrated into a MILP optimization using Gurobi. Co-simulated in TRNSYS-MATLAB, the controller reduced electricity costs by 1.82–18.65%, improved thermal comfort (RMSE down by 0.35 °C), and achieved flexibility factors up to 0.648.
Cai et al. [107]	An aging-aware MPC minimized battery degradation and utility cost in a commercial building. Using real data and convex optimization, it achieved 9% utility savings and 39% less battery wear.
D'Ettorre et al. [108]	This MPC optimized a hybrid heating system (HP, boiler, TES) using MILP. Longer prediction horizons supported larger storage sizes and yielded up to 8% cost savings in synthetic simulation.
Langer et al. [109]	A MILP MPC using Julia controlled PV, BESS, TES, and HPs in a smart home. Adding a battery raised self-sufficiency from 52% to 79%, with seasonal optimization achieved under real-time constraints.
Drgona et al. [110]	A real-life MPC field test in a GEOTABS office combined QP optimization and cloud-based SCADA. It achieved 53.5% heat pump energy savings and 36.9% comfort improvements over rule-based control.
Baniasadi et al. [111]	Hybrid MPC used PSO for sizing and MILP for real-time control of BSS and TSS. In real-lab validation, it cut annual electricity costs by over 80% and life-cycle costs by 42%.
Wirtz et al. [112]	A MILP-based MPC for 5GDHC controlled 17 buildings using Python. Real weather and demand data revealed up to 60% cost savings in July compared to free-floating temperature operation.
Gholami et al. [113]	This MPC scheduled a solar collector, PCM exchanger, and backup heater using EnergyPlus and SCIP. Using Auckland weather data, it saved 12–57% in heating costs, with best results in residential buildings.

Table 3. *Cont.*

Author	Summary
Jin et al. [114]	A bi-level MPC was introduced for Community BEMS, coordinating heating demand and pricing. Using MILP reformulated via MPEC dualization, the upper layer optimized operator profit while the lower minimized user costs. Real data from China showed better economic balance than fixed pricing, validated via Monte Carlo simulations.
Hou et al. [115]	A white-box NMPC enhanced with weather error modeling was used for HVAC in a Norwegian university. Simulations showed 3.4% heating cost reduction and 73% fewer comfort violations during forecast uncertainty.
Chen et al. [116]	A nonlinear MPC using PMV-based comfort and renewable sources (PV, GSHP, battery) was applied to a multi-zone academic building. Real data simulations yielded up to 19% cost savings and high comfort compliance.

Table 4. Key attributes of gray-box MPC applications for BEMS.

Ref.	Year	Type	Solver	FH/TS	Baseline	Equipment	Building	Zone	Data	Testbed	Sim Tools	Cit.
[117]	2015	Stohastic	NLP	5 h/15 m	RBC	HVAC	Library	8/1	Real	Real	N/A	201
[118]	2015	Classical	QP	2.5 h/5 m	RBC	HVAC	Mall	5	Real	Sim	N/A	85
[119]	2015	Economic	NLP	24 h/1 h	MPC	HVAC	Commercial	3	Real	Sim	N/A	85
[120]	2015	Classical	NLP	30 m/15 m	PID	HVAC	Office/Lab	32	Real	Sim	Simulink	122
[121]	2015	Classical	MILP	6 h/1 h	RBC	N/A	Office	5	Real	Sim	EnergyPlus	77
[122]	2016	Robust	NLP	24 h/15 m	PI	HVAC	Laboratory	1	Real	Real	N/A	88
[123]	2016	ML-based	QP	24 h/1 h	Fixed	RES/ESS	Resident	1	Real	Sim	Custom	101
[124]	2016	Classical	PSO	24 h/15 m	Fixed	HVAC	Office	5/15	Real	Sim	EnergyPlus	93
[125]	2016	Classical	NLP	56 d/1 h	N/A	HVAC	Office	1	Real	Sim	N/A	148
[126]	2016	Classical	MILP	4 h/15 m	Fixed	HVAC/RES/ESS	Commercial	1	Synth	Sim	N/A	284
[127]	2016	Classical	NLP	24 h/5 m	RBC	HVAC/HP	Office	1	Real	Real	Modelica	161
[128]	2016	ML-based	QP	2 h/5 m	MPC/PI	HVAC	Office	1	Real	Real	N/A	76
[129]	2016	Classical	MILP	4 h/10 m	MILP	HVAC	Office	3/100	Real	Sim	EnergyPlus	141
[130]	2017	Classical	QP	1 d/15 m	MPC	HVAC	Resident	1	Real	Sim	EnergyPlus	70
[131]	2017	Stohastic	MINLP	1 h/5 m	Fixed/MPC	PV/EV	Resident	1	Real	Sim	N/A	79
[132]	2017	Economic	LP	3 d/1 h	PI	HVAC	Residents	10	Real	Sim	EnergyPlus	73
[133]	2017	Classical	GA	2 h/15 m	RBC	HVAC/DHW/HP	Multi	8	Real	Real	EnergyPlus	78
[134]	2017	Hierarchical	MILP	1 h/5 m	RBC	HVAC/RES	Resident	1	Real	Sim	N/A	113
[135]	2017	ML-based	QP	8 h/30 m	RBC	HVAC/DWH/RES	Resident	1	Real	Sim	N/A	161
[136]	2018	Classical	QP	5 h/30 m	Heuristic	RES/EV	Mixed	5	Real	Sim	N/A	93
[137]	2018	Economic	MILP	7 d/1 h	RBC/PID	HVAC/TSS	University	500	Real	Both	N/A	98
[138]	2018	Classical	MIQP	6 h/15 m	N/A	HP/PV/ESS	Resident	1	Real	Sim	N/A	100
[139]	2018	Classical	QP	24 h/1 h	Fixed	RES/ESS	Commercial	1	Real	Sim	N/A	91
[140]	2018	Classical	NLP	24 h/15 m	MPC	HVAC	Resident	100	Synth	Sim	N/A	117
[141]	2018	ML-based	N/A	N/A	MPC/Fixed	HVAC/RES/ESS	Resident	1	Real	Sim	N/A	128
[142]	2019	Classical	QP	2 h/15 m	RBC	HVAC	University	4	Real	Sim	TRNSYS	137
[143]	2019	Stohastic	QP	5 h/1 h	MPC	HVAC	University	4	Real	Sim	N/A	119
[144]	2019	Robust	MILP	24 h/30 m	Fixed	HVAC/RES/ESS	Mixed	9	Real	Sim	N/A	108
[145]	2018	Classical	NLP	7 d/15 m	N/A	HVAC	Room	1	Real	Sim	COBYLA	73
[146]	2019	Economic	NLP	24 h/15 m	PID	HVAC/RES/DHW	Resident	1	Real	Sim	N/A	108
[147]	2019	Classical	QP	2 d/1 h	Fixed	DH/DHW	Residents	1	Real	Sim	Custom	94
[148]	2019	Classical	Sim	-/10 m	Fixed	HVAC	N/A	1	Real	Sim	EnergyPlus	86
[149]	2019	Classical	MILP	12 h/10 m	RBC	HVAC	Mixed	126	Real	Sim	EnergyPlus	94
[150]	2019	Classical	QP	24 h/15 m	Fixed	HVAC/RES/ESS	Mixed	4	Real	Sim	Simulink	83
[151]	2019	Classical	NLP	24/15 m	PI	HVAC	N/A	1	Both	Sim	Modelica	86
[152]	2019	RL-based	KKT	3 h/15 m	P	HVAC	Conference	1	Real	Sim	EnergyPlus	126
[153]	2020	Classical	NLP	24 h/1 h	RBC	HVAC/HP/DHW	Resident	1	Real	Real	N/A	73
[154]	2020	Classical	QP	4h/2m	Fixed	HVAC	University	1	Real	Real	N/A	108
[155]	2020	Classical	MILP	24 h/1 h	RBC	HVAC/RES/Grid	Marina	3	Real	Sim	N/A	84
[156]	2020	Classical	MILP	24 h/14 m	Fixed	HVAC/HP/TSS	Resident	1	Real	Sim	N/A	75
[157]	2021	Stohastic	MINLP	24 h/1 h	RBC	HP/RES/EV	Resident	1	Real	Sim	N/A	71
[158]	2021	ML-based	Evol.	1 h/1 h	SVM/ANN	RES/ESS	Resident	1	Real	Sim	PyGMO	93
[159]	2021	Classical	NLP	48 h/30 m	RBC	HVAC	Office	7	Real	Real	Modelica	62
[160]	2021	Classical	GA	-/1 h	RBC	HVAC	University	1	Real	Real	Modelica	76
[161]	2022	RL-based	N/A	24 h/15 m	RL/MPC	HVAC	Resident	1	Real	Sim	Modelica	126
[162]	2022	ML-based	QP	6 h/30 m	RBC	HVAC	Resident	2	Real	Real	N/A	59
[163]	2022	Classical	NLP	24 h/10 m	PI	HVAC	Office	4	Real	Real	Modelica	102
[164]	2022	Classical	NLP	24 h/5 m	RBC	HVAC/ESS/Other	Store	4	Real	Real	Modelica	67
[165]	2022	Classical	QP	12 h/1 h	PI	HVAC	Store	1	Real	Sim	Custom	50
[166]	2023	ML-based	N/A	60 d/15 m	RBC	HVAC/Lights	School	-	Real	Sim	Dynamo	65

Table 5. Summaries of Gray-box MPC applications for BEMS.

Author	Summary
Ma et al. [117]	Introduces SMPC with bilinear ARMAX under uncertain loads. Two chance constraint methods are compared. Validated in real HVAC tests with 22.5% energy savings.
Mantovani et al. [118]	Gray-box nonlinear MPC applied to a shopping center. Accounts for HVAC actuator nonlinearity and RES tracking. Achieves 4.5% energy savings and 70% stratification drop.
Mai et al. [119]	Economic MPC for HVAC reserve provision in commercial buildings. Robust formulation under uncertainty with profit objective. Validated using PJM prices and synthetic signals.
Liang et al. [120]	Classical MPC using ARMAX for AHU in office buildings. Centralized control in multi-zone setup. Yields 27.8% energy savings over PID control.
Feng et al. [121]	MPC for radiant slab cooling using evaporative tower. MILP solved in co-simulation with EnergyPlus. Energy savings over 50% and comfort maintained.
Vrettos et al. [122]	Hierarchical MPC for HVAC-driven frequency regulation. Integrates robust MPC, reserve scheduler, and fan control. Validated in FLEXLAB with RMSE = 0.42 °C.

Table 5. *Cont.*

Author	Summary
Sun et al. [123]	Nonlinear MPC strategy integrating RBF-NN-based load forecasting and battery degradation modeling, achieving 35.8% reduction in cost and 36.9% reduction in carbon emissions compared to a fixed grid-only baseline.
Li et al. [124]	Multi-objective MPC using white-box model and HJPSO. Pre-cooling strategy under TOU pricing. Achieved up to 84% cost savings in simulations.
Harb et al. [125]	Grey-box thermal modeling with various RC structures. Best performance achieved by 4R2C model. Applicable to MPC with minimal prior knowledge.
Gu et al. [126]	Two-layer online MPC with ARIMA forecasting and MILP. Used in CCHP system with multiple energy units. Saved over 10% in operational costs.
De Coninck et al. [127]	Real-life MPC deployment in hybrid heating system. Used Modelica-based grey-box modeling. Saved 34–40% cost with 20–30% energy savings.
Chen et al. [128]	Adaptive MPC with dynamic thermal sensation model. Incorporates real-time occupant feedback via EKF. Saved 25% energy over PMV-based control.
Bianchini et al. [129]	White-box MILP-based MPC for DR in large buildings. Heuristic zone-based decoupling improves scalability. Maintains comfort with 4% cost penalty vs. full MILP.
Shi et al. [130]	Occupancy-aware MPC using logistic regression models. User-defined penalty balances comfort and efficiency. Saved 8% electricity vs. baseline MPC.
Rahmani-Andebili [131]	Multi-time-scale stochastic MPC with neural forecasts. Dual-layer controller manages deferrable loads. Cut weekly cost by over 50% vs. single-scale MPC.
Pedersen et al. [132]	E-MPC for structural storage-based DR in apartments. Both centralized and decentralized controllers tested. Shifted 2 kWh/m^2 and cut cost by 6%.
Hilliard et al. [133]	Hybrid MPC with EnergyPlus and random forest models. Implemented with user feedback in real buildings. Reduced electric use by 29% and thermal by 63%.
Fiorentini et al. [134]	Hybrid MPC for net-zero home with PCM and PVT systems. MLD formulation with hierarchical structure. Improved comfort and energy savings experimentally.
Jin et al. [135]	User-centric MPC for HEMS with lightweight QP solver. Forecasts user behavior and DR events. Saved 7.6% energy and improved DR participation.
Yang et al. [136]	Decentralized MPC for EV charging with wind matching. EBDC algorithm reduces grid load by 68%. Scalable to 1000 EVs with minimal performance loss.
Rawlings et al. [137]	Hierarchical economic MPC for large-scale HVAC with MILP. Aggregated upper layer and zone-level lower control. Applied to 25 buildings, saving 10–15% cost.
Killian et al. [138]	Gray-box MIQP MPC for smart homes with full HVAC-PV-BESS integration. Uses POD-based occupancy prediction and dynamic constraints. Reduces grid use and improves thermal balance.
Mbungu et al. [139]	Adaptive MPC for commercial PV-BESS systems under TOU tariffs. Gray-box QP formulation with time-partitioned control. Achieves 46–49% grid cost reductions in South Africa.
Jiang et al. [140]	Gray-box MPC for smart HVAC in grid-connected buildings. Formulated as SOCP for cost and grid stability. Improved voltage and reduced OLTC switching.
Luo et al. [141]	Three-stage HEMS with ANN forecast and MPC correction. Uses NAA metaheuristic and adaptive PMV model. Minimized HVAC cost and deviation using real data.
Tang et al. [142]	MPC with rolling horizon for DR events using chillers and PCM. Gray-box linear state-space model with Gurobi solver. Improved comfort and demand stability in 2 h windows.
Shang et al. [143]	Data-driven SMPC with SVC-based uncertainty sets. Robust optimization for HVAC under stochastic disturbances. Reduced energy and complexity versus classical SMPC.
Lv et al. [144]	Rolling robust MPC for energy coordination in CIES. MILP solved every 30 min under TOU pricing. Achieved 2.7% cost savings while maintaining comfort.
Brastein et al. [145]	Parameter estimation for grey-box MPC in small buildings. Uses COBYLA optimizer and reduced-DOF strategy. RMSE between 0.5 and 1.5 °C in experimental validation.
Kuboth et al. [146]	Economic MPC for floor-heated homes with PV and BESS. Distributed NLP solvers improve computation. Cut costs 11.6%, raised PV use and system efficiency.
Hedegaard et al. [147]	Bottom-up urban-scale gray-box MPC with MCMC calibration. Tested on 159 Danish homes, simulating price-based DR. Achieved 5% peak reduction with scalable accuracy.
Chen et al. [148]	Gray-box MPC for NV and HVAC control via Python/Scikit-learn. Simulated in five climates using BCVTB and EnergyPlus. Saved 17–80% energy with zero discomfort hours.
Bianchini et al. [149]	Centralized MPC with two-stage MILP for HVAC-PV-Storage DR. Simulated on 126-zone eight-floor building. Saved up to 35.67% and kept zone violations <0.14 °C.
Biyik [150]	Multi-zone deterministic MPC co-optimizing HVAC, PV, and BES. QP solves multi-objective cost with MATLAB/Simulink. Reduced peak load 23% without comfort loss.
Blum et al. [151]	Single-zone grey-box MPC exploring modeling sensitivities. Simulated under time-varying pricing using Modelica/BCVTB. Found 20% cost swing based on model setup.
Chen et al. [152]	Gnu-RL: differentiable MPC + RL with PPO imitation learning. Controlled radiant HVAC in sim and real testbed. Saved 6.6–16.7% energy with improved comfort.
Finck et al. [153]	Real-life EMPC for HP and TES with hybrid modeling. Used MATLAB; achieved up to 15% cost savings. Enabled demand-side flexibility KPIs.
Carli et al. [154]	IoT-based grey-box MPC for lab HVAC via MATLAB quadprog. Real-time closed-loop deployment with 2 min sampling. Saved 18.6% energy, raised comfort to 95.4%.
Carli et al. [155]	MILP-based MPC for marina microgrid with HVAC and BESS. Used MATLAB/CPLEX; saved 8.2% annually. Improved self-supply and load scheduling.

Table 5. *Cont.*

Author	Summary
Fitzpatrick et al. [156]	MPC with MILP for hybrid heating under tariff schemes. Applied to real German house with HP+TES+boiler. Flex up to 1370 kWh, at PEE increase of 9.1%.
Yousefi et al. [157]	Stochastic nonlinear MPC for HEMS with PV-PEV-HP. MLP forecasts + MINLP via APOPT solver. Saved up to 34%, reached 97% ideal performance.
Shivam et al. [158]	Res-DCCN gray-box PEMS with MOEA/D-DE optimizer. Multi-goal: cost, SoC, CO2. $R^2 > 0.93$ on forecasts. Savings up to 199.87% vs. baseline.
Freund [159]	Gray-box NLP MPC with R7C4 model in Hamburg office. Used fmincon; cut heating energy 30%, 75% in April. Comfort mostly within DIN EN 15251 Cat II.
Clausen et al. [160]	GA-optimized MPC with DT integration in lecture room. Controlled HVAC using Controleum with real-time data. Improved efficiency, enabled smart ventilation.
Arroyo et al. [161]	RL-MPC combining DDQN and gray-box MPC in BOPTEST. Outperformed standalone RL in constraints and cost. Handled dynamic pricing with one-step MPC horizon.
Bünning et al. [162]	Compared ARMAX, RF, ICNN in MPC for Swiss flat. ARMAX had better efficiency, lower error, 26–49% savings. Used QP via CVXOPT in 156-day experiment.
Blum et al. [163]	MPCPy-based UFAD control in 6000 m² office, achieving 40% HVAC savings over PI, with multi-zone control. Showed modeling + deployment effort breakdown.
Zhang et al. [164]	Gray-box MPC for PV-BESS HVAC in California SMB. Used JModelica/IPOPT; saved 12%, cut peaks 34%. SPO platform handled TOU and grid events.
Bird et al. [165]	AWS-based MPC retrofitted to UK retail store HVAC. Low-order ARX with MQTT and cloud infra. Saved 650 kWh, $240; low-carbon gains.
Hosamo et al. [166]	DT-MPC with Bayesian networks for FM and fault prediction. ANN-based faults predicted 2 months early (97% accuracy). Applied in two smart Norwegian public buildings.

Table 6. Key attributes of black-box MPC applications for BEMS.

Ref.	Year	Type	Solver	FH/TS	Baseline	Equipment	Building	Zone	Data	Testbed	Sim Tools	Cit.
[167]	2015	Classical	NLP	48 h/30 m	Fixed	HVAC/RES/TSS	Office	1	Real	Sim	TRNSYS	97
[168]	2015	Classical	MILP	24 h/30 m	RBC	HVAC	Office	1	Synth	Sim	EnergyPlus	62
[169]	2015	ML-based	Heuristic	2 h/10 m	Fixed	HVAC	Airport	4	Real	Sim	N/A	126
[170]	2015	ML-based	GA	8 h/15 m	RBC/Fixed	HVAC	Office	3	Synth	Sim	EnergyPlus	65
[171]	2016	Classical	GA	24 h/10 m	RBC	HVAC	Resident	-	Synth	Sim	EnergyPlus	107
[172]	2017	Heuristic	GA	24 h/1 h	RBC	HVAC	Resident	-	Synth	Sim	EnergyPlus	66
[173]	2018	Hierarchical	LP	12 h/5 m	Fixed	HVAC	Room	1	Real	Sim	SARIMA	119
[174]	2018	ML-based	QP	40 m/10 m	RBC/MPC	HVAC	Resident	1/22	Both	Both	EnergyPlus	281
[175]	2018	ML-based	GA	24 h/1 h	RBC	HVAC	Office	6	Synth	Sim	EnergyPlus	213
[176]	2019	ML-based	Heuristic	2 h/15 m	RBC/Fixed	HP/DHW/RES/TSS	Resident	12	Real	Sim	EnergyPlus	160
[177]	2019	ML-based	MILP	24 h/10 m	Fixed	HVAC/RES/ESS	Resident	5	Real	Sim	Simulink	63
[178]	2019	ML-based	GA	24h/1h	Fixed	HVAC/TSS	University	60	Real	Sim	Modelica	125
[179]	2019	ML-based	DP	12 h/1 h	PI	HVAC/HP/RES	Resident	1	Real	Real	N/A	102
[180]	2019	ML-based	LM	5 m/5 m	Fixed	HVAC	Resident	-	Real	Sim	EnergyPlus	63
[181]	2020	ML-based	NLP	1 h/2 m	PID	HVAC	Office	1	Real	Real	Simulink	245
[182]	2020	ML-based	QP	1 h/2 m	PID	HVAC	Office	1	Real	Real	Simulink	62
[183]	2020	ML-based	N/A	1 h/1 h	RF/SVR	HVAC	University	3/4	Real	Sim	Python	180
[184]	2021	ML-based	LM	1 h/5 m	Fixed	HVAC	Office	1	Real	Real	Simulink	71
[185]	2021	ML-based	GBDT	1 h/1 h	SVM/ANN	HVAC	Commercial	1	Real	Real	N/A	80
[186]	2022	ML-based	PSO	15 m/5 m	Fixed	HVAC	University	-	Real	Sim	N/A	71
[187]	2022	ML-based	QP	45 m/15 m	Fixed/RBC	HVAC	Gym	1	Synth	Sim	EnergyPlus	85
[188]	2022	ML-based	Bayesian	24/1 h	RBC/MPC	RES/ESS/EV	Resident	1	Synth	Sim	N/A	57
[189]	2023	RL-based	SAC	5 m/5 m	RBC	HVAC	Office	1	Real	Sim	OpenAI	106
[190]	2023	ML-based	NLP	6 h/10 m	RBC/MPC	HVAC	Office	5	Real	Sim	EnergyPlus	40

Table 7. Summaries of black-box MPC applications for BEMS.

Author	Summary
Li et al. [167]	A black-box MPC using subspace 4SID modeling was implemented to optimize heating setpoints for TES in a BIPV/T integrated office building. TRNSYS-MATLAB simulations showed a 34.5% reduction in heat pump energy and up to 45.4% in total energy when PV was included.
Lee et al. [168]	A NARX-based MPC framework was developed for HVAC demand response using MILP and neural forecasting. Simulations showed 30.95% cost savings versus rule-based control using ESS and EGS under synthetic dynamic pricing.
Huang et al. [169]	This ANN-based MPC used NARX-MLP structures to model HVAC dynamics in a four-zone airport terminal. Real-weather-data-driven simulations achieved 28% daily and 10% monthly energy savings compared to baseline strategies.
Garnier et al. [170]	MPC using feedforward ANNs trained via cascade-correlation optimized HVAC in a three-zone French building. Compared to five baselines, it reduced winter energy use by 15% and summer by 5%, while halving discomfort.
Ascione et al. [171]	A simulation-based MPC using EnergyPlus and MATLAB applied genetic algorithms to balance cost and thermal comfort. Compared to rule-based control, it achieved 56% operating cost savings and 8–11% comfort improvement.
Ascione et al. [172]	This framework co-optimized building design and control using GAs with EnergyPlus–MATLAB co-simulation. Results showed 72.8% primary energy savings and nearly EUR 7000 lifecycle cost reductions compared to baselines.
Tavakoli et al. [173]	A two-stage hierarchical MPC was developed for BEMS in a commercial microgrid with wind power and 100 PEVs. The first stage uses LP with CVaR for PEV charging under price uncertainty; the second stage allocates energy deterministically. Simulations using SARIMA-based forecasts and real electricity prices showed 32.47–37.67% cost savings.

Table 7. *Cont.*

Author	Summary
Smarra et al. [174]	A random-forest-based data-driven MPC replaced physical models with regression trees, yielding DR tracking error under 3% and 25.4–49.2% energy savings in real and simulated case studies.
Reynolds et al. [175]	A decentralized ANN-GA MPC optimized heating setpoints per zone in a six-zone office. Simulations with real weather data showed 25–27% energy or cost savings versus rule-based baselines under TOU tariffs.
Pallonetto et al. [176]	This ML-driven MPC used MP5 regression trees and heuristic pruning for DR scheduling in a 12-zone Irish bungalow. Results showed 39% energy, 49% cost, and 38% CO_2 savings over thermostatic control.
Megahed et al. [177]	NNPC combined ANN forecasting with MILP control for a ZEB in Egypt. Achieved full grid-independence on critical days and EGP 57.5 k net savings over lifecycle while ensuring comfort and stability.
Cox et al. [178]	ANN-based MPC controlled district cooling with TES on a university campus. Real validated simulations showed 16.5% cost savings under TOU and 14.2% under RTP versus no-TES strategy.
Finck et al. [179]	ANN-based EMPC was tested in a Dutch home for demand flexibility. Field results showed improvements in flexibility indicators (FF from −0.88 to 0.67) and better alignment of loads with dynamic pricing.
Lee et al. [180]	ANN-based control adjusted VAV DAT setpoints to reduce cooling load in a multi-zone office. Achieved 21.5% chiller energy and up to 18% total HVAC energy savings over fixed DAT strategy.
Yang et al. [181]	An adaptive ANN-based MPC with SQP and ESM optimization was deployed in two NTU Singapore buildings. Delivered 58.5% and 36.7% energy savings over BMS/thermostats with improved comfort and real-time learning.
Yang et al. [182]	Implemented a linear MPC in a real lecture theater to control both AHU and DOAS-assisted SSLC systems. Using QP optimization, Kalman filtering, and real-time occupancy and weather forecasts, the MPC achieved up to 20% energy savings and improved comfort over PID-based BMS.
Wang et al. [183]	A stacked ensemble combining RF, GBDT, XGBoost, SVR, and kNN predicted energy use in two educational buildings. Real-data testing improved MAPE by up to 49.4% and showed R2 > 0.92, outperforming individual ML models.
Yang et al. [184]	This approximate MPC used NARX RNNs to emulate MPC actions, replacing costly optimization. Real building tests showed 51.6–36.2% energy savings and >100× faster execution than traditional MPCs.
Zhang et al. [185]	GBDT was used for cooling load prediction in a multi-zone ice-storage HVAC system. Real monitored data showed 37% accuracy gain over DNN/SVM, proving its effectiveness for load forecasting in predictive control.
Afroz et al. [186]	A NARX-PSO MPC minimized HVAC energy while preserving IAQ (CO_2, VOCs) and thermal comfort in a multi-zone university building. Real data showed 7.8% annual HVAC energy savings with ASHRAE compliance.
Elnour et al. [187]	NN-MPC was developed for a university sports hall optimizing HVAC setpoints and occupancy. Achieved 46% energy savings while maintaining acceptable PMV and IAQ in simulations using a calibrated EnergyPlus model.
Petrucci et al. [188]	LSTM-driven MPC coordinated DERs at community level via a centralized agent. Simulations in Rome showed 21% DR-period demand cut and 15% reduced grid bidirectionality using synthetic weather/load data.
Zhuang et al. [189]	An RL-based MPC framework combined SAC control with LSTM forecasting for HVAC optimization. Real IoT data showed 17.4% energy and 16.9% PMV improvement in a smart office testbed using deep surrogate models.
Xiao et al. [190]	The model combined RNN and LSTM layers with physics-based constraints and applied to a five-zone office building to optimize HVAC operation, reducing energy use and improve thermal comfort. Compared to On/Off and LSTM-MPC baselines, it achieved up to 8.9% energy savings and 64% comfort improvement, using simulations in EnergyPlus with real-world data.

6. Evaluation per Key Attribute

A thorough evaluation of MPC within BEMS requires a multidimensional analysis across several essential key attributes. Such dimensions offer insight into technical robustness, practical deployment potential, and innovation level. By judging these attributes across different dimensions, the current review uncovers trade-offs, modeling diversity, and scalability potential. More specifically, the key attributes that MPC is being judged on include the following:

- **Modeling Trends:** The modeling paradigm employed within MPC for BEMS—whether white-box, gray-box, or black-box—is a cornerstone of the controller's operational accuracy, interpretability, and deployment viability. The model functions as an internal predictive mechanism, simulating the building's thermal and energy dynamics in response to control inputs such as HVAC signals, solar irradiance, occupancy levels, and ambient conditions. The choice of model type is depicted in Section 6.1, reflecting the different trade-offs encountered in the research.
- **MPC Type Trends:** Section 6.2 illustrates the occurrences and trends considering the different MPC types. By focusing on the different types of MPC—classical, stochastic, robust, economic, hierarchical, ML-based, and RL-based—the evaluation reveals how each type addresses uncertainty, complexity, and control objectives. The MPC type shapes controller flexibility and adaptiveness, but also indicates implementation bottlenecks related to computation, reliability, and integration in real-life building systems.

- **Optimization Solvers:** In MPC for BEMS, the solver portrays the computational engine that transforms mathematical formulations into actionable control signals. The solver's ability to handle linearity, convexity, and integer constraints affects real-time viability and system responsiveness. Section 6.3 reveals occurrences, trends, and limitations regarding the use of different MPC optimization solvers in the recent literature.
- **Baseline Control:** Section 6.4 highlights the different tendencies in baseline control utilization, underlining the lack of standardization. Baseline strategies—such as fixed, RBC, PID, or even existing BMS—act as reference benchmarks and validate the proposed MPC approaches. Comparing MPC to such methodologies enables quantifiable assessment of control improvements in energy efficiency, peak shaving, comfort, and more.
- **Performance Indexes:** Evaluating MPC effectiveness in BEMS hinges on selecting meaningful performance metrics. These include energy and cost savings, comfort maintenance, emission reduction, model accuracy, flexibility, and computational feasibility. Tracking these metrics across studies, as detailed in Section 6.5, illustrates the shifting focus in smart building control—from simple thermal regulation to multi-objective optimization under uncertainty. To this end, the dedicated subsection on performance indexes and their tendencies in the research provides the interested reader with key trends and opportunities in current performance evaluations.
- **Equipment Types:** The equipment controlled by different energy systems, such as HVAC, RES, ESS, DHW, LS, or EVs, defines the system's operational dynamics and optimization constraints. According to evaluation, modern MPC approaches are expanding from HVAC-only control to multi-energy systems reflecting the growing complexity and integration level of modern BEMS. More trends and elaborate details on the utilization of different energy systems and their integrations may be found in the dedicated Section 6.7.
- **Building Types:** The type of building (residential, commercial, institutional, etc.) affects occupancy patterns, thermal inertia, and control priorities. Analyzing BEMS by building type, as detailed in Section 6.8, helps contextualize design priorities and assess the generalization capabilities of MPC architectures.
- **Number of Building Zones:** Single-zone control is computationally lighter but less representative of real operational challenges. Multi-zone and high-zone-count model implementations demonstrate the ability of MPC to scale but often face challenges in modeling fidelity and solver tractability. To this end, Section 6.9 identifies the different key trends in the field considering the number of zones in MPC applications, as a way to reflect the spatial complexity of the optimization problems.
- **Testbed Types:** Whether the results are validated through simulation, real-world deployment, or both directly affects the credibility and applicability of each work. Simulations enable flexible scenario testing, while real-world deployments test robustness under uncertainty and operational constraints. In order to identify different tendencies, Section 6.10 elaborates on real-life deployment, while also providing useful suggestions considering the status of MPC.
- **Software Tools:** Optimization and simulation environments enable model construction, data integration, and co-simulation with optimization solvers. The choice of tool impacts model detail, integration complexity, and runtime performance, and often reflects institutional familiarity rather than optimality. Grounded in the importance of such tools for MPC, Section 6.11 presents a comprehensive evaluation of the various optimization and simulation environments, offering interested readers a clear overview of the current landscape.

6.1. Modeling Trends

The evaluation shows that white-box MPC has maintained a steady presence in academic research over the past decade (see Figure 6, right), but its use in real-world applications remains limited. Although large-scale studies confirm that these models can deliver highly accurate thermal predictions, their practicality decreases as system complexity and diversity increase. For example, Hedegaard et al. [147] achieved accurate results using a 5R2C thermal model across 159 buildings in simulation but also emphasized the significant calibration effort required for large-scale deployment. This highlights a recurring challenge: while white-box models offer scientific precision, they often lack scalability. In comparison, gray-box MPC has become the most widely used modeling approach in recent years, appearing in roughly twice as many studies as white-box methods (see Figure 6). This trend reflects a preference for models that balance experimental reliability with manageable data and calibration requirements. Gray-box models also support adaptability through online learning and physics-informed neural networks [117,186,190], making them more practical for deployment. Meanwhile, black-box MPC has seen growing adoption over the past decade (see Figure 6, right), with applications ranging from multi-zone systems to urban-scale implementations [169,175,188]. These models are often used to coordinate various energy resources and have consistently outperformed traditional rule-based or PID controls. Reported benefits include HVAC energy savings of up to 58% and emission reductions of over 38% [179,186,189], many of which have been validated with real-world operational data—further demonstrating the growing maturity and deployment readiness of data-driven MPC solutions.

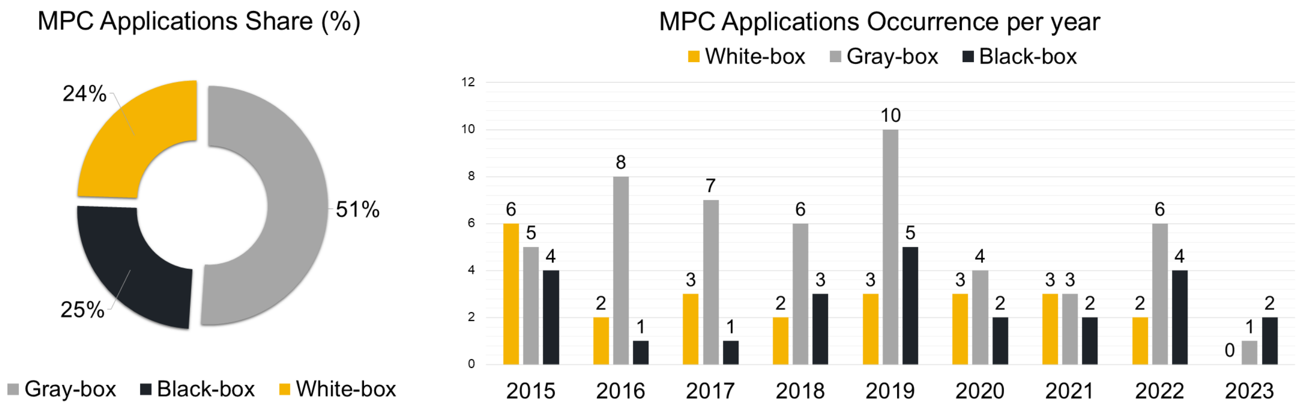

Figure 6. (**Left**) White-, gray-, and black-box share (%) in MPC applications. (**Right**) White-, gray-, and black-box MPC highly cited applications occurrence per year.

As is evident from the evaluation, recent studies indicate that different MPC modeling approaches are increasingly associated with distinct solver strategies. White-box models continue to rely primarily on convex optimization techniques like QP and MILP, while gray- and black-box models are increasingly paired with metaheuristic and learning-based solvers, such as genetic algorithms (GA), particle swarm optimization (PSO), and reinforcement learning (RL) [172,187,189]. Such evidence reflects a broader shift toward multi-objective MPC, where competing objectives—such as cost, comfort, emissions, and energy consumption—are optimized simultaneously [171,179]. Forecasting strategies also differ notably across model types: white- and gray-box MPC often depend on external weather forecasts or statistical prediction tools, whereas black-box approaches increasingly integrate forecasting components directly into the control framework—using models like LSTM, random forests, or ensembles [183,185]. This embedded structure enhances robustness to forecast errors and improves real-time performance, particularly under uncertain or demand-responsive conditions.

Despite these advances, several recurring challenges remain. Real-time adaptive modeling is still underused, with most implementations relying on static, offline-trained models. This limits their ability to respond to sensor faults, changing occupancy, or seasonal variability [173,174,181,186]. While gray-box models show increasing promise, the field still lacks standardized methodologies and large-scale validations [166,175,184,190]. Especially in black-box MPC, the rapid expansion of model architectures (e.g., ANN, LSTM, RF, ensemble methods) often occurs without careful justification or sensitivity analysis, raising concerns about reproducibility and safety in deployment. Another significant gap lies in the absence of consistent modeling protocols. Variability in feature selection, time resolution, and performance metrics makes it difficult to compare results across studies [169,170,176,185]. Moreover, few studies have explicitly examined the trade-offs between increasing model complexity and its effects on efficiency, occupant comfort, or computational cost [117,167,172,179]. Finally, an emerging concern is the potential impact of model inaccuracies or structural uncertainties as they propagate through the MPC loop—posing risks to reliability and occupant comfort [174,178,180,189].

6.2. MPC Type Trends

The analysis indicates that deterministic approaches—particularly classical and economic MPC—have historically dominated MPC applications in building energy management systems (BEMS), largely due to their compatibility with white- and gray-box models and their reliance on efficient convex solvers like QP and MILP [155,179] (see Figure 7, left). However, their prevalence is gradually decreasing, especially in multi-zone scenarios where the inability to manage uncertainty limits their effectiveness. Although robust and stochastic MPC were developed to address this gap by incorporating uncertainty via chance constraints or probabilistic forecasts [117,173], their use remains mostly confined to simulations or academic prototypes due to high computational costs and integration complexity. **Economic MPC** has found use in specific cost-focused applications, such as dynamic pricing and peak load control [175,176,191] (see Figure 7, left). However, its practical application is hindered by the non-convex nature of its objectives, which affects solver performance, and a lack of robust validation under real-world conditions or forecast uncertainty [168,171].

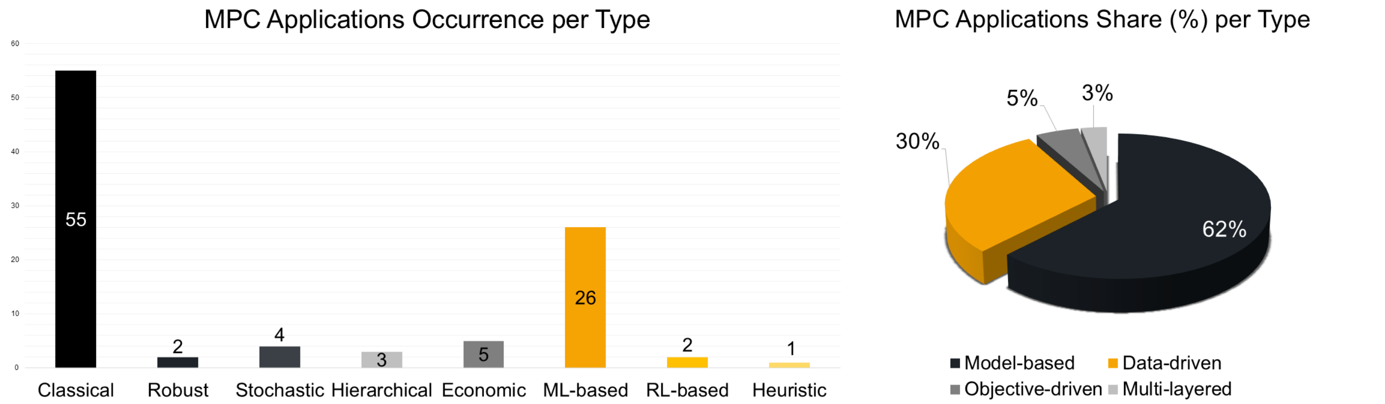

Figure 7. (**Left**) MPC type occurrence in the overall applications. (**Right**) MPC type share (%) in the overall applications.

Since 2018, there has been a sharp rise in **ML-based MPC**, particularly using black-box models like ANNs to represent building dynamics, paired with a variety of solvers—from convex optimizers to heuristic algorithms [169,174,186]. While simulation studies report positive results, real-world deployment still faces challenges, particularly around seasonal adaptability and robustness to uncertainty [181,188]. **RL-based MPC** has also shown promise for handling complex and dynamic control problems [166,189], but real-world use remains limited due to ongoing concerns around convergence reliability, safety, and constraint satisfaction in critical systems. Similarly, heuristic and evolutionary solvers such as GA and PSO are frequently used in black-box, multi-objective MPC implementations [170,172,187] (see Figure 7, left and right), though their application is mostly limited to offline or proof-of-concept scenarios due to their high computational demands.

Across all MPC types, adaptability emerges as a critical bottleneck. Most models remain static, trained offline, and degrade in performance when exposed to evolving building conditions such as occupancy variability, seasonal changes, or system aging [174,181,186]. Hybrid approaches—such as physics-informed ML models and gray-box surrogates—have been proposed as a compromise; however, such frameworks are still underexplored and lack robust field validation [166,190]. In addition, stochastic MPC has rarely been combined with advanced ML forecasting, leaving a fragmented pipeline that underutilizes predictive potential [117,173]. RL-based methods also face unresolved challenges in transferability, policy stability, and safety, all of which hinder deployment in real BEMS [166,189]. Finally, benchmarking practices remain inconsistent, with the majority of studies continuing to compare against outdated rule-based or PID baselines (see Section 6.4), a practice that restricts comparability and limits the generalizability of findings [168,179].

6.3. Optimization Solvers

Among the most commonly adopted variants, MILPs were primarily utilized for managing discrete decisions—such as HVAC on/off states, energy storage scheduling, or EV charging coordination (See Figure 8, left). According to the evaluation, the structured nature of MILP solvers, combined with powerful commercial tools like CPLEX and Gurobi, has made them a staple in both residential and commercial BEMS contexts [99,104,105,129,137]. MILP has also readily supported hierarchical or distributed MPC frameworks, enabling modular expansions in multi-agent systems [134,155]. However, as systems scale or require fine-grained time resolution, solver runtimes may grow prohibitively long, especially in the presence of nonlinear dynamics [140,162].

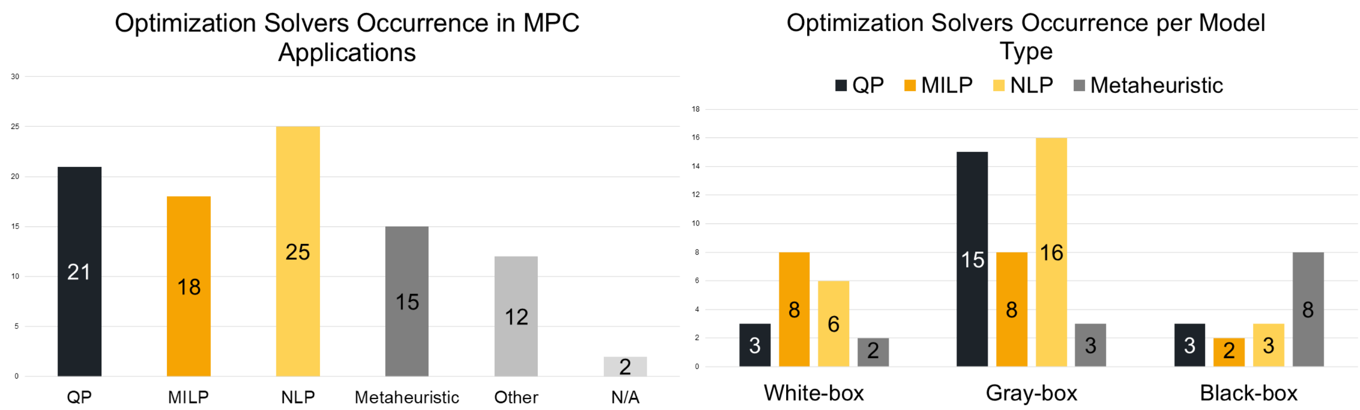

Figure 8. (**Left**) Optimization solver type occurrence in MPC applications. (**Right**) Optimization solver type occurrence in white-, gray-, and black-box MPC applications.

For scenarios demanding detailed physical modeling—such as nuanced thermal behaviors or nonlinear actuator dynamics—NLP solvers like IPOPT offered a solution. Such approaches seem to be especially efficient when integrated with simulation environments such as Modelica or Simulink [97,98,115,164,178,181]. Where system behavior was linear and the cost function was quadratic, QP solvers—especially CVXOPT and OSQP variants—offered rapid and reliable solutions, particularly for comfort-centric or energy-minimization use cases [102,130,159]. QP solvers, though, suffered from structural rigidity and were unable to handle integer variables or piecewise objectives without reformulation—a fact that potentially limited their applicability in more complex scheduling tasks.

In contrast, metaheuristic solvers like GAs and evolutionary programming were increasingly used in black-box MPC applications (See Figure 8, right) where gradient information was unavailable [111,172,178,186]. However, since such approaches commonly suffered from high computational cost, most of their implementations were limited to offline, prototypical scenarios. To this end, critical details like runtime performance and convergence behavior often went unreported in the concerned applications. A promising yet underutilized class of solvers included sequential quadratic programming (SQP) and interior point methods (IPM)—notably, frameworks such as CasADi combined with IPOPT. Such solvers may support sparse matrices and automatic differentiation, a fact that renders them suitable for deploying in hybrid or RL-based MPC strategies in real time [107,128,161,164,190]. However, according to the evaluation, their adoption remained confined to specific areas, limiting their impact within the broader BEMS research.

It is evident that solver-agnostic modeling platforms like YALMIP, CVX, and Pyomo/PyGMO have undeniably made MPC development more accessible and streamlined over the past decade [95,116,135,158]. Although such tools simplified implementation and promoted rapid prototyping, they often concealed important solver-related configurations. Details such as warm-start strategies, convergence thresholds, or sensitivity settings were rarely documented in the literature, prohibiting the reproduction of results or benchmark performance across studies. Most importantly, there is a noticable gap in the literature when it comes to systematically comparing solvers under uniform MPC formulations. Solver choices were often implemented without justification in the vast majority of works, and thus, there was limited understanding of how different solvers perform relative to model complexity, control horizons, or uncertainty handling.

6.4. Baseline Control

The most dominant baseline in the field remains **rule-based control** (See Figure 9, left). This deterministic logic, typically implemented through static temperature thresholds or time schedules, was heavily used due to its simplicity and its ubiquity in legacy BMS platforms. RBC appeared extensively in both early and recent MPC studies across all modeling domains. Notable examples include [94], who benchmarked their EnergyPlus-co-simulated white-box MPC in a 20-zone office building against RBC, and [99], who controlled a residential HVAC and RES setup using an RBC comparator. Similar uses can be found in [105,106,110,114], who consistently showed that MPC is adequate to significantly reduce energy consumption and maintain indoor comfort compared to RBC. This reliance on RBC baselines reflected its entrenched position in practice and its suitability as a conservative baseline. However, this tendency also exposes a gap: RBC is often implemented in its most naive form, with minimal adaptive scheduling or occupancy-informed rule updates—a fact that may lead to overstating MPC's relative advantage. Another deterministic-type baseline control methodology is the **fixed setpoint**—or on/off control schemes—particularly in studies targeting residential or single-zone implementations (see Figure 9, left). This methodology replicates thermostatic logic, where HVAC operation is triggered once a fixed threshold is crossed. Studies such as [103,123,181,184] adopted this minimalist control logic to represent typical household systems. While easy to implement and highly interpretable, fixed control schemes provide limited realism for comparison, especially as modern thermostats increasingly incorporate learning and adaptive behavior. The risk here is methodological: using overly simplistic baselines, which can inflate MPC performance metrics—especially in simulations where the predictive capabilities of MPC are unfairly compared to reactive or poorly tuned benchmarks.

In larger commercial and industrial buildings, **PID** and PI controllers were commonly utilized as a baseline mean, aligning more closely with the infrastructure found in real-world BMS deployments (See Figure 9, left). Such feedback loops are adequate to offer better disturbance rejection than RBC but still lack predictive capabilities. Studies by [122,151,160] employed PI or PID as benchmarks for HVAC control under physical constraints. Similarly, ref. [146] evaluated MPC for a residential hybrid RES-DHW system against a traditional PID controller. Despite being closer to operational reality, a common limitation of PID baselines concerns the absence of adaptive or auto-tuned PID schemes, which exist in modern BMSs and could provide a fairer and more challenging baseline. Their exclusion introduces a subtle bias in favor of MPC's perceived superiority, a gap that future work should also address.

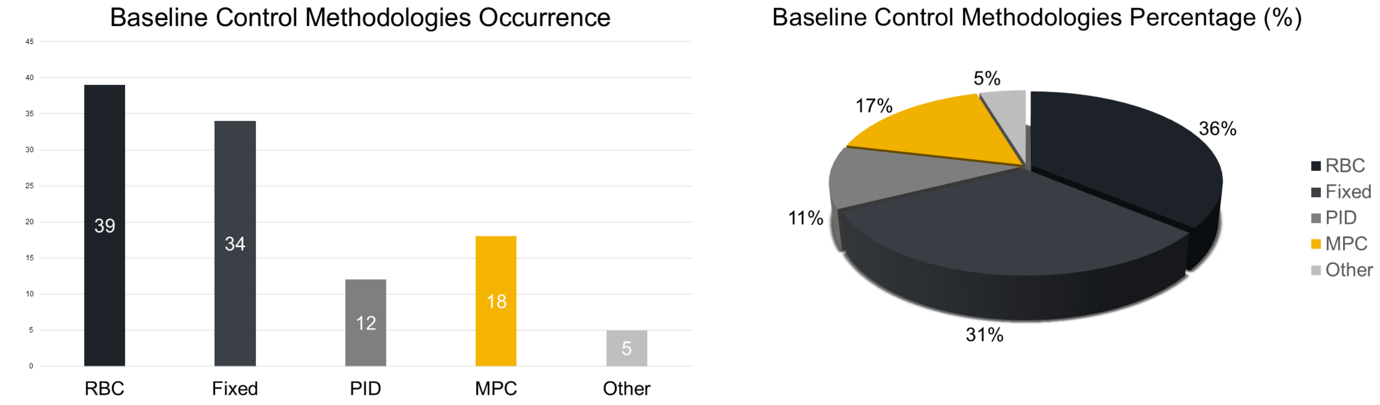

Figure 9. (**Left**) Baseline control methodology occurrence in MPC applications. (**Right**) Baseline control types share (%) in MPC applications.

An emerging and scientifically significant trend considers the use of basic MPC as a baseline for more sophisticated variants, such as robust, stochastic, or learning-based MPC. This is evident in studies like [102], where a classical linear MPC is compared to an MPC with aging-aware constraints, or in [107], which evaluates degradation-aware economic MPC against conventional predictive strategies. Moreover, in [161], researchers validated the proposed RL-based controller against both RBC and deterministic MPC, illustrating how predictive control has become the default standard against which intelligent extensions are now measured. This evolution illustrates the maturity of MPC in the research community, but it also complicates benchmarking. Potential limitations could include the clearly delineated modeling assumptions as solver configurations, and forecast uncertainty—which were often only superficially documented.

More recently, a limited but promising set of studies has introduced ML-based baselines, where controllers powered by ANNs, SVMs, or DTs were used not only for prediction but also for control. For instance, ref. [185] compared a gradient-based DT-MPC against SVM and ANN surrogates, while [158,183] benchmarked evolutionary MPC policies against multiple ML baselines, including kNN, XGBoost, and random forests. Such comparisons were significant since they reflect the ongoing convergence of ML and MPC, particularly in black-box or data-rich environments. Their implementation as baseline controls is, however, limited in the literature (See Figure 9, right): few studies rigorously compare model-based vs. model-free control in the same environment under the same data assumptions. Moreover, ML-based baselines often lack real-time safety guarantees and stability analysis, making them difficult to evaluate on par with deterministic MPC.

Crucially, the literature reveals a near-complete absence of dynamic, adaptive, or market-aware baselines. Very few studies benchmark MPC against controllers that respond to real-time electricity prices, occupancy predictions, or dynamic DR signals. This is important given the strong policy emphasis on demand flexibility and grid-interactive efficient buildings. Notable exceptions included [106], which integrated dynamic pricing into the baseline logic, and [188], which evaluated MPC under smart grid trading scenarios. The field lacks a systematic approach to incorporate demand-response-capable baselines or context-aware policies, leaving a research gap between MPC's theoretical potential and its real-world deployability under time-varying tariffs and grid constraints.

6.5. Performance Indexes

According to the evaluation, energy and cost savings remain the most commonly reported performance indicators across all MPC modeling categories (see Figure 10, left and right). Such savings were typically expressed as absolute values or percentages, with some cases—such as those in [94,117,184]—reporting reductions ranging from 17% to over 50%. It should be mentioned that such figures were often presented without adequate context regarding climatic conditions, electricity tariffs, or occupancy dynamics, a fact that limits their generalizability and hinders cross-study comparisons.

Thermal comfort was also frequently assessed in the concerned papers, but with considerable variation in how it is defined and applied. Out of the total studies, a significant amount of implementations included comfort-related metrics (see Figure 10, right); commonly used indicators included PMV, PPD, indoor temperature deviations, and discomfort hours. Few works incorporated other comfort-related factors such as indoor air quality or daylight access, which points to an ongoing lack of holistic performance evaluations in occupant-centric building control. Contrary to energy, cost, and comfort, environmental-related metrics such as CO_2 emissions remained underrepresented in white- and gray-box MPC, despite the increasing urgency of decarbonization efforts. Notable exceptions include [176], who attempted to tie control strategies to real-time carbon intensity signals. Additionally, energy savings were often assumed to equal environmental benefits, overlooking how grid emissions change over time and missing a chance to align MPC strategies with carbon reduction goals.

The importance of predictive accuracy was also evident—especially for gray-box MPC—where model fidelity is a cornerstone. Statistical measures like RMSE, CVRMSE, R^2, MAE, and MBE appear commonly (see Figure 10, left), as evidenced in [117,183,190]. Yet, despite the high amount of efforts, only a few studies attempted to link prediction error directly to critical outcomes like energy overshoot or discomfort events, reflecting a disconnect between modeling accuracy and real-world performance impacts. On the contrary, metrics assessing grid interaction and flexibility appeared less common, despite MPC's inherent capability for demand-side responsiveness. Moreover, only a handful of studies evaluated aspects like peak shaving, load shifting, or integration into demand response programs. Examples such as [179,188,192] proposed methods for assessing these capabilities, but consistent metrics like flexibility factors or ramp rate limits were rarely used, undermining the comparability of such features across different control designs. Computation and deployment-related metrics were also noticeably sparse. Runtime performance, control loop frequency, scalability of solvers, and financial metrics like payback periods or return on investment were reported in only a small subset of studies (typically two to four per model category). Yang et al. [184] and Ascione et al. [171] were among the few addressing these practical concerns. This fact is particularly concerning for black-box MPC, which often involves complex models with uncertain computational behavior—an issue that may become a major barrier to real-world implementation.

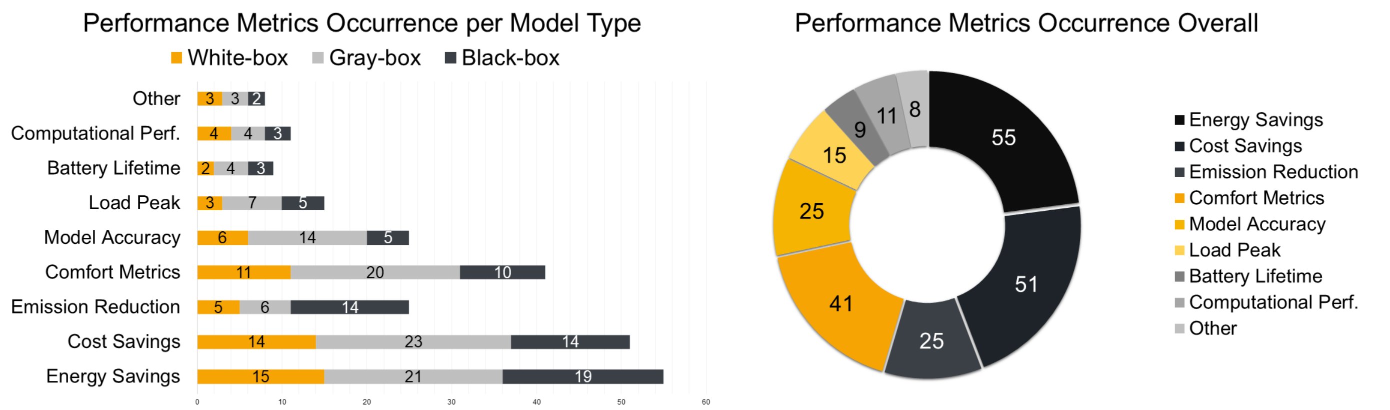

Figure 10. (**Left**) Performance metrics occurrence per white-, gray-, and black-box MPC applications. (**Right**) Performance metrics occurrence in MPC applications overall.

6.6. Performance Comparisons

When evaluating the comparative value of MPC against various baseline controllers—such as rule-based control (RBC), fixed schedules, PID control, or even alternative MPC formulations—it is essential to establish a consistent justification framework. In this review, comparisons are made only against the same type of baseline control, ensuring that reported improvements are assessed in a fair and meaningful manner. Naturally, these comparisons are not absolute, as each study is conducted under different conditions, including varying testbeds, climates, building types, and system configurations. Nevertheless, the performance analysis presented here offers a relative indication of which innovations have delivered the most substantial gains within their respective contexts, allowing common patterns to emerge across diverse experimental settings. To support this, our justification approach considers four key dimensions: (i) the magnitude of improvement in energy use, cost, or emissions; (ii) enhancements in comfort, flexibility, or grid service capabilities; (iii) methodological novelty or the expansion of MPC objectives (e.g., integration of occupant feedback, asset degradation modeling, or multi-scale scheduling); and (iv) the strength of supporting evidence, with greater weight given to real-world implementations over purely simulated results.

By incorporating these dimensions, the selection of top-performing studies reflects not only the scale of numerical improvements but also the robustness, generalizability, and innovative value of the contributions made to the field.

- **MPC against RBC baselines:** The most notable improvements of MPC over rule-based control (RBC) in BEMS are found in [110,112,121,162,172]. These studies were selected for reporting the highest gains in energy, cost, and comfort—often supported by real-world experiments or detailed simulations. For example, Ascione et al. [172] demonstrated a 72.8% reduction in primary energy, marking the largest absolute gain under simulation. Drgona et al. [110] validated MPC benefits in a real office building, achieving 53.5% lower heat pump energy use and 36.9% improvement in comfort. Feng et al. [121] showed 55% cooling tower energy savings while maintaining over 95% comfort compliance, highlighting MPC's dual benefit. In advanced district systems, Wirtz et al. [112] reported 59.7% cost savings using MPC in 5GDHC networks, and Bünning et al. [162] observed 26–49% energy savings in real-world settings with physics-informed MPC. These results are particularly important as they demonstrate not only high energy and cost savings but also verified comfort improvements, directly addressing both efficiency and occupant well-being. Near-top contributions include Razmara et al. [95], De Coninck et al. [127], and Smarra et al. [174], which reported

25–40% savings but were rated lower due to either simulation-only validation or narrower performance focus.

- **MPC against fixed-based baselines:** Significant improvements of MPC over fixed control strategies are evident in [100,111,124,131,184]. Baniasadi et al. [111] reported an 80.4% reduction in annual electricity cost and 42.4% in life cycle cost, demonstrating MPC's long-term economic potential. Li et al. [124] achieved up to 83.9% cost savings in small buildings, highlighting scalability across different climates. Salakij et al. [100] obtained 42.6% HVAC energy savings, proving the effectiveness of reduced-order models. Yang et al. [184] experimentally validated 51.6% and 36.2% cooling energy savings in two building types, with improved comfort. Rahmani et al. [131] emphasized time-resolution impacts, with a multi-time-scale stochastic MPC achieving a 52.4% reduction in weekly operating cost, outperforming both fixed and single-scale MPC baselines. These results are especially relevant given the continued prevalence of fixed strategies in practice.
- **MPC against MPC-based baselines:** Advances of MPC over other MPC formulations are highlighted in [107,128,190]. Xiao et al. [190] introduced a physics-consistent deep learning MPC, which outperformed reduced-order and neural network MPCs—achieving moderate energy savings but substantial reductions in comfort violations, showing the value of improved model fidelity. In [128], an occupant-feedback-driven MPC reduced energy use by 25% compared to a PMV-based approach, demonstrating the effectiveness of human-in-the-loop control. Cai et al. [107] integrated battery aging considerations into economic MPC, reducing degradation without increasing utility costs, illustrating the benefits of broader objective integration. Other strong contributions include Jiang et al. [140], who embedded grid objectives to improve voltage stability and cost, and Rahmani et al. [131], whose multi-scale MPC outperformed single-scale control by 20%. Shang et al. [143] presented a robust, data-driven MPC that achieved consistent gains over other robust strategies by reducing conservatism in uncertainty modeling.
- **MPC against PID-based baselines:** Key improvements over PID controllers are demonstrated in [120,122,163]. Blum et al. [163] implemented a gray-box MPC that reduced HVAC energy consumption by 40% compared to an existing PI controller over a two-month period, validating performance under real conditions. Liang et al. [120] showed nearly 28% energy savings using an ARMAX-based MPC, highlighting the benefit of predictive optimization over reactive PID control. Vrettos et al. [122] replaced PI-based zone control with hierarchical robust MPC, reducing thermal tracking errors while enabling frequency regulation. Although not directly energy-focused, the study demonstrated comfort and grid service improvements. Other relevant contributions include Kuboth et al. [146], reporting over 11% lower operating costs using distributed MPC; Rawlings et al. [137], who achieved 10–15% cost reduction with hierarchical economic MPC in real infrastructure; and Blum et al. [151], who reported up to 10% cooling energy cost savings. These findings confirm that MPC consistently outperforms PID control in energy, cost, and comfort—across various building scales and applications.

Table 8 presents the leading MPC applications identified in the literature, which achieved substantially higher performance compared to other approaches.

Table 8. Top 15 MPC research application achievements compared to different baselines.

Author	Baseline	Performance Achievement
Ascione et al. [172]	RBC	72.8% reduction in primary energy and lifecycle savings compared to RBC setpoints.
Drgona et al. [110]	RBC	53.5% reduction in heat pump energy and 36.9% thermal comfort improvement in a real office.
Feng et al. [121]	RBC	55% cooling tower energy savings and 26% pumping savings, with >95% comfort compliance.
Wirtz et al. [112]	RBC	Up to 59.7% cost savings vs RBC and 143% improvement vs fixed temperature control.
Bünning et al. [162]	RBC	26–49% energy savings in real-life experiments across heating and cooling modes.
Baniasadi et al. [111]	Fixed	80.4% electricity cost reduction, 42.4% life cycle cost reduction, and 28% smaller battery size.
Li et al. [124]	Fixed	Up to 83.9% cost savings in small buildings and 46.7% in medium buildings compared to Fixed control.
Salakij et al. [100]	Fixed	42.6% energy savings with variable HVAC and 37.4% with on/off HVAC compared to Fixed constant setpoints.
Yang et al. [184]	Fixed	51.6% and 36.2% cooling energy savings in office and lecture theater vs. thermostatic fixed baselines.
Rahmani et al. [131]	Fixed	52.4% lower weekly cost than the fixed baseline, and 19.8% better than single-scale MPC.
Xiao et al. [190]	MPC	Outperforms SSM- and LSTM-based MPCs with 4.5–8.9% lower energy and 59–64% fewer comfort violations.
Chen et al. [128]	MPC	Dynamic thermal sensation MPC achieves 25% lower energy than PMV-based MPC in controlled experiments.
Cai et al. [107]	MPC	Aging-aware EMPC cuts battery degradation by 39% vs conventional EMPC (MPC-I).
Blum et al [163]	PID	energy consumption reduced 40% over a two-month real-world period compared to PI.
Liang et al. [120]	PID	ARMAX-based MPC achieved 27.8% average energy savings compared to the installed PID baseline.

6.7. Equipment Types

According to the analysis, single-energy-system frameworks were predominant, with HVAC systems serving as the primary representative (see Figure 11, right). To this end, HVAC-only control appears as the foundational scheme of MPC across gray- and black-box modeling frameworks. Pioneering examples, such as [97,130,134,159], illustrated its use in single-zone testbeds. Leveraging QP or MILP for rapid computation, such implementations were typically targeted at balancing thermal comfort with energy or cost objectives, employing either first-principles thermal models or data-driven regressions. Heat pump research application implementations aligned with sector-wide electrification trends. Vertical studies—such as [110,114,144]—incorporated HPs into MPC designs, often in conjunction with RES and ESS. According to the evaluation, HPs illustratd both continuous modulation and discrete on/off challenges that favored mixed-integer approaches within MPC frameworks (see Figure 11, left). Notably, multi-energy-system frameworks—representing integrated BEMS—were more common than single-energy-system frameworks within white-box MPC implementations (see Figure 11, center). This tendency reflected the modeling strengths of white-box approaches, which naturally support detailed representations of interconnected energy systems. Moreover, white-box MPC are common in design-stage studies, where multi-energy integration is feasible and encouraged. Additionally, such MPC studies are typically research-driven, favoring complexity and completeness over scalability.

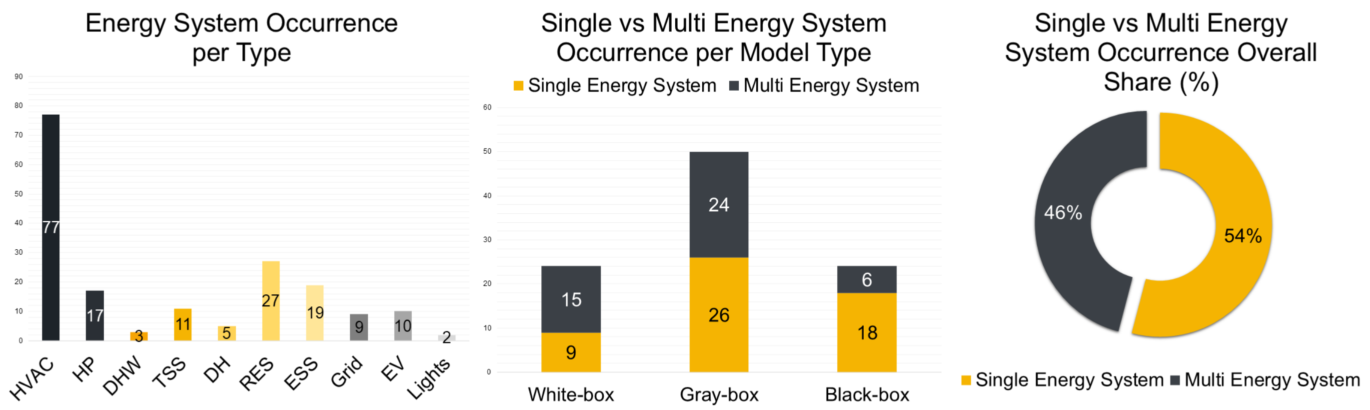

Figure 11. (**Left**) Energy system type occurrence in MPC applications. (**Center**) Single vs. multi-energy system frameworks occurrence for white-, gray-, and black-box MPC applications. (**Right**) Single- vs. multi-energy-system frameworks share (%) in MPC applications.

Another commonly controlled energy system framework was RES—commonly integrated with ESS (see Figure 11, left). Studies such as [98,105] extended MPC models to include PV generation and battery or thermal storage for load shifting. In the research efforts of [138,177], RES and ESS co-operation was further coordinated under mixed-integer formulations. Such efforts employed economic or hybrid MPC variants, reflecting growing multi-objective ambitions. Leveraging thermal inertia and demand flexibility was also common in the literature. For instance, in [129,137], researchers exploited storage in district heating or DHW systems to provide demand flexibility. Similarly, refs. [173,178] demonstrated analogous strategies using phase change materials (PCM). Such implementations typically utilized prediction horizons of up to several days to enable energy shifting strategies rather than immediate setpoint control, contrary to the majority of the MPC applications.

Even less common in the literature, EV integration and community-scale energy management was an emerging frontier. Research applications such as [131,155,188] perceive EVs as controllable loads or energy sources, signaling convergence with mobility and community energy objectives. In such cases, MPC architectures often relied on stochastic or hierarchical schemes to accommodate user behavior and travel schedules. Last but not least, non-thermal loads and lighting were limited in the MPC domain. Although less common, works like [94,166] demonstrated visual comfort control via lighting systems. Such efforts expanded BEMS toward comprehensive indoor environmental quality (IEQ), integrating occupant-centric factors—even where the thermal inertia of such systems was minimal.

In summary, the evolution from HVAC-only setups to multifaceted configurations involving hybrid energy systems, mobility, and occupant well-being has demonstrated MPC's expanding potential. Enabled by advances in QP and MILP, stochastic optimization, real-time analytics, and digitalization, modern MPC frameworks are gradually transitioning from single-equipment control to orchestrating complex, sector-coupled, grid-integrated systems in order to more efficiently portray real-world building settings. However, a noticeable gap persists in the adoption of multi-agent or decentralized MPC paradigms. Despite the increasing complexity and interconnectedness of modern BEMS, only 3 out of nearly 100 highly cited studies implemented decentralized or distributed control schemes. Such limited occurrence is significant, particularly considering that distributed architectures are theoretically better suited for modular and scalable control in integrated BEMS (IBEMS) frameworks—or in multi-zone or multi-building models. This trend may arise from challenges in algorithmic coordination, communication latency, and system stability assurance—issues not yet widely addressed in the current literature.

6.8. Building Types

According to the analysis, residences dominate the reviewed MPC literature, consistently appearing across white-, gray-, and black-box implementations (see Figure 12, center and right). This focus aligns with the increasing interest in smart home energy systems that integrate RES, ESS, and occupant behavior into control frameworks [99,104,134,138,176,188]. Office buildings and university facilities were also well represented (see Figure 12, left). Offices, with their relatively stable occupancy and substantial HVAC loads, served as ideal environments for studying energy–comfort trade-offs [94,101,124,159], while university campuses often provided equipped testbeds for real-world MPC validation [97,98,154,178].

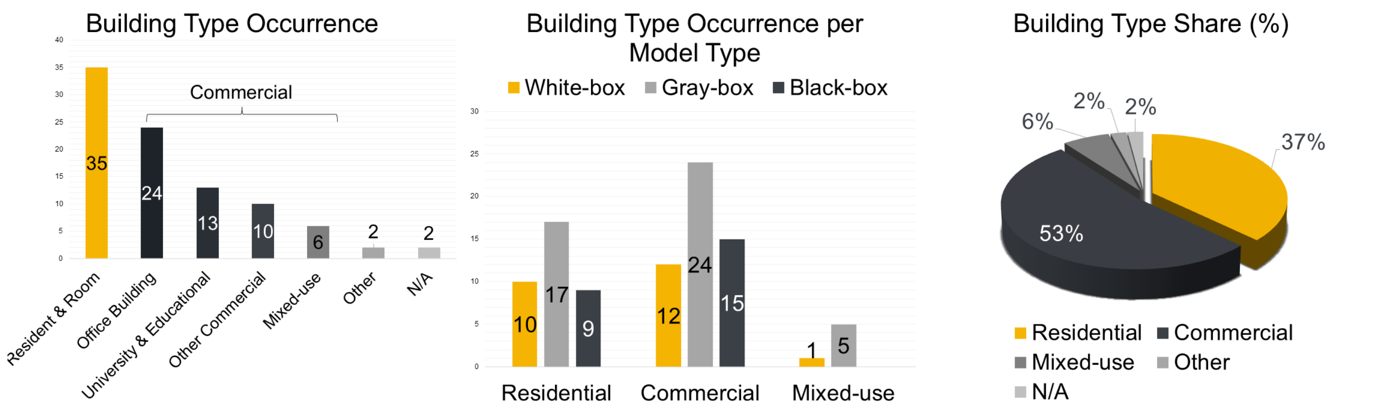

Figure 12. (**Left**) Building types occurrence in MPC applications. (**Center**) Building types occurrence per white-, gray-, and black-box MPC applications. (**Right**) Building types share (%) in MPC applications.

Mixed-use buildings, commercial sites, and retail spaces/stores were significanty less frequent in MPC research, despite their considerable energy footprints. Their complexity—stemming from varied occupancy, zoning, and equipment—likely contributes to this underrepresentation (See Figure 12, left and right). Domain-specific applications were also sparse: mosques [103], libraries [117], conference centers [152], and gyms [187] illustrated tailored MPC designs. Moreover, unique environments like airports [169] and marinas [155] also demonstrated MPC's expansion into specialized settings.

Overall, the distribution of building types underscores a clear research trend: moving from controlled, homogeneous settings (offices and campuses) toward more variable, occupant-centric environments (homes). Residential studies are prevalent due to the relative affordability and simplicity of deploying small-scale, simulation-based MPC systems. In comparison, commercial and retail applications often demand multi-agent architectures, hierarchical control, and increased adaptivity—features that entail higher computational and implementation complexity and thus remain less frequently demonstrated in practice. This pattern reflects both the current technological maturity and the research community's shift toward empowering end users and integrating buildings into responsive, grid-interactive frameworks.

6.9. Number of Zones

The number of zones modeled in MPC-based applications reflects a crucial aspect of system spatial resolution, directly influencing model detail, computation burden, and choice of control structures. Single-zone building cases dominated (see Figure 13, left), highlighting a lack of maturity in addressing the complexity of multi-zone building models. It seems that early-stage studies tend to simulate single- or low-zone scenarios (1–10 zones)—common in residential settings—due to their relative simplicity. Examples include [123,130,134,138], all implementing MPC in single-zone environments, commonly using gray-box MPC (see Figure 13, right). The aforementioned setups facilitated a primary focus on algorithm development, solver behavior (e.g., QP, MILP), and core performance metrics (energy saving, thermal comfort) under simplified sensor-actuator configurations. In contrast, multi-zone MPC applications—though represented in fewer studies (see Figure 13, center)—addressed more complex and realistic building scenarios. For instance, with regard to medium-zone-number cases (20–50) in [94], researchers applied a 20-zone white-box MPC using EnergyPlus in an actual office building. Similarly, in [120], scientists implemented 32 gray-box ARMAX zones, while [137] coordinated multiple university campus zones via hierarchical MPC. Moreover, in [140], MPC handled 100 zones with synthetic data, showing scalability potential. Smarra et al. [174] compared building types with 1-, 22-, and 4-zone configurations, highlighting the need for algorithm robustness across layouts. Moreover, large-scale zone modeling (considering more than 50 zones), identified in Bianchini et al. [129,149] (100+ zones) and Cox et al. [178] (60 zones), promoted the deployment of advanced optimization tools (CPLEX, Gurobi, IPOPT), hierarchical control structures, and co-simulation platforms like EnergyPlus, Modelica, and Dymola.

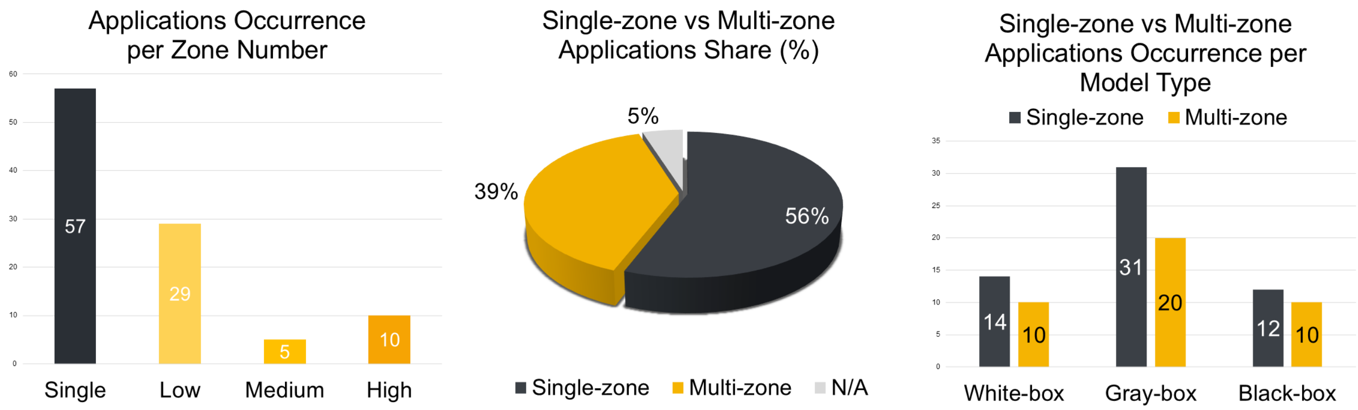

Figure 13. (**Left**) MPC applications occurrence per zone number. (**Center**) Single zone vs. multi-zone MPC applications share (%). (**Right**) Single-zone vs. multi-zone MPC applications per white-, gray-, and black-box MPC.

A recent shift extends zoning beyond thermal partitioning. Megahed et al. [177] and Zhang et al. [164] illustrated multi-zone building models control coordinating HVAC with RES and ESS in spatially distinct zones in residential and commercial buildings. This trend reflects the emergence of zones as autonomous energy micro-systems, each with local objectives and limited observability—paving the way for multi-agent MPC and RL approaches. In summary, zone granularity has not been merely an architectural consideration but a defining factor in MPC's scalability, performance, and implementation readiness. The field is clearly moving from centralized, single-zone testbeds (e.g., [97,146]) toward zone-resolved distributed controllers, suitable for operational deployment in extensive, heterogeneous building environments (e.g., [137,140,178]).

6.10. Testbed Types

The environment in which MPC is deployed—whether simulated or real-world—significantly influences its demonstrated maturity and practical relevance. While simulative applications afford precision and controlled testing, they often fail to capture the complexities and uncertainties of real operational contexts. According to the evaluation, most reviewed studies remained simulation-based (see Figure 14, right), especially the ones concerning white-box MPC approaches (see Figure 14, left) and co-simulation platforms like EnergyPlus, TRNSYS, or Modelica. Examples include Yang et al.'s deterministic MPC analysis [181], Baniasadi et al.'s MILP-driven multi-zone control [105], and Cai et al.'s economic dispatch framework accounting for battery degradation [107]. Moreover, ML-based or RL-based MPC innovative applications—such as [161,174,190]—were typically confined to simulated environments, largely due to integration challenges with non-convex or opaque models. Black-box MPC methods, in particular, appeared overwhelmingly simulation-centric, as their reliance on data-driven patterns often conflicted with concerns over interpretability and real-world robustness. Similarly, stochastic and economic MPC frameworks, despite tackling uncertainty and market dynamics, were rarely deployed beyond simulated scenarios [117,131,138], due to complex data needs and computational demands.

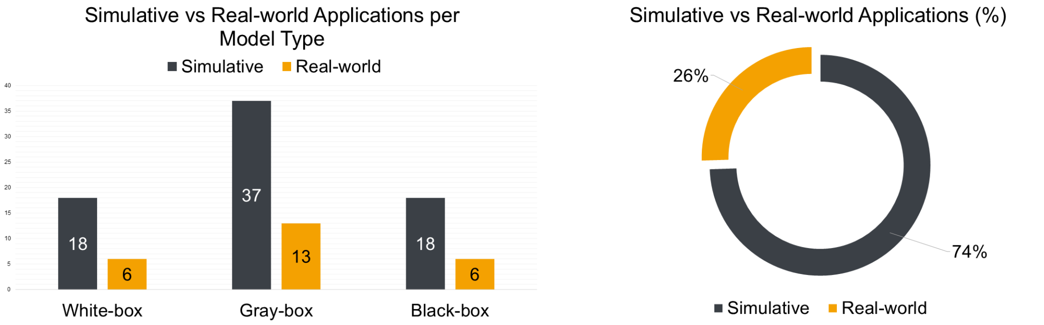

Figure 14. (**Left**) Simulative vs. real-world applications occurrence for white-, gray-, and black-box MPC. (**Right**) Simulative vs. real-world applications share % for MPC.

In contrast, gray-box models dominated in real-world applications (see Figure 14, left). Such implementations—although fewer—validated more mature, physically grounded frameworks using gray-box or reduced-order models. Pioneering field deployments include Sturzenegger et al.'s Swiss office building controller [94], Goyal et al.'s MPC in Singapore lecture halls [97], and Picard et al.'s work in Canadian commercial facilities [102]. More recent examples by Freund et al. [159] and Hou et al. [115] employed Modelica-integrated MPC in real-time applications, showcasing the reliability of RC-based models under MILP or QP solvers. Such hybrid evaluations—pairing simulation with on-site validation—offered rare insights into real-world implementation gaps, including sensor noise, actuator delays, and model miscalibration issues.

As concerns the optimization solvers' utilization, MILP and QP appeared across both simulated and field studies, whereas heuristic methods (e.g., GA, RL) remained entirely simulation-based, since they are primarily utilized in black-box MPC. Moreover, real-world deployments appeared limited to HVAC control within institutional facilities. In contrast, more complicated BEMS frameworks—involving RES, ESS, or EVCS coordination—remained predominantly unexplored in actual operation [140,146,155]. As concerns FH and TS, it is noticeable that experimental testbeds often used longer timesteps (15–30 min) and shorter forecast horizons (2–6 h), contrasting with the higher resolution (5 min intervals, longer horizons) typical in simulations. It seems that real-life practical limitations—like sensor update rates, actuator delays, and computational limitations—prohibited high-frequency control. In contrast, simulations were able to afford finer resolutions and longer horizons since they had operated without real-time physical constraints.

6.11. Software Tools

Optimization Platforms: MATLAB continued to act as the primary environment for MPC development (see Figure 15, right), supported by toolboxes like YALMIP, CVX, and Simulink, and solvers such as Gurobi, CPLEX, quadprog, and IPOPT. The platform was widely employed in classical and economic MPC frameworks as well as in robust and stochastic designs, supporting real-time testing and parametric optimization. MATLAB's versatility was demonstrated across numerous studies involving both simulation and experimental validation. Python has seen a significant rise, particularly in black-box MPC, ML, and RL applications. With libraries such as CasADi, CVXPY, Pyomo, TensorFlow, and OpenAI Gym, Python enabled the design and deployment of adaptive control systems. Python was frequently coupled with simulation environments like EnergyPlus and Modelica via middleware (e.g., BCVTB), enabling closed-loop co-simulation and data exchange. Studies leveraging Python seem to typically explore advanced solver development, model training, and RL-based agent deployment.

Simulation Environments: EnergyPlus stands out as the most used simulation engine due to its detailed modeling of HVAC systems, building envelopes, and internal conditions (see Figure 15, left). This tool is extensively applied in both white- and gray-box models, often in conjunction with MATLAB through BCVTB for real-time closed-loop control. Some research also incorporates MLE+ and GenOpt for optimization-integrated design workflows. Moreover, Modelica was increasingly favored for high-fidelity, component-based simulation, offering real-time and multi-physics modeling capabilities. Tools like Dymola and OpenModelica were used for simulating HVAC, thermal networks, and energy storage systems. JModelica played a supporting role in optimization tasks where symbolic representations and solvers like IPOPT and CasADi are needed, especially for nonlinear MPC formulations.

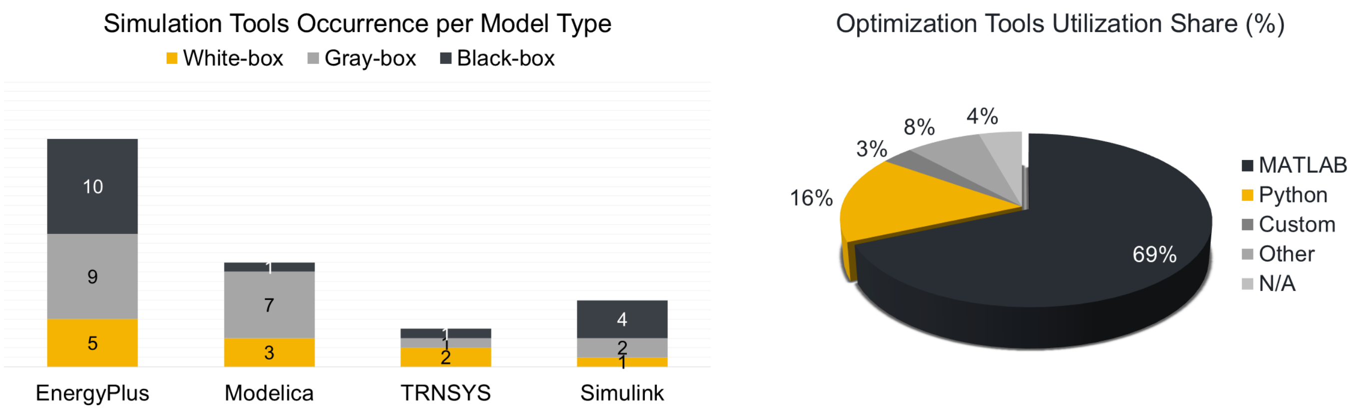

Figure 15. (**Left**) Simulation tools occurrence for white-, gray-, and black-box MPC, and (**Right**) Optimization tools and utilization (%) in MPC applications.

MATLAB integrated with EnergyPlus via BCVTB was the most common toolchain setup for MPC tuning and closed-loop validation, especially in gray- and black-box designs. An increasingly popular alternative involved Modelica-based simulation paired with Python optimization, which proved effective for nonlinear and real-time implementations. Pure Python workflows dominated in ML-based and RL-based MPC applications, leveraging libraries like TensorFlow and PyTorch. Additionally, MATLAB-only configurations remained frequent in gray-box MPC using ARX/ARMAX or ANN surrogate models for predictive control. Such practices reflected a broader trend towards flexible, interoperable software ecosystems. It seems that the landscape of tools supporting MPC research in BEMS has evolved into a robust yet dynamic ecosystem. MATLAB maintains its foundational role in control development; EnergyPlus and Modelica deliver simulation accuracy; and Python is advancing rapidly in adaptive and learning-based control research. This interplay enables researchers to tackle increasingly complex, data-rich, and real-time challenges in the development of intelligent energy management systems.

7. Discussion

A comprehensive review of the recent literature on MPC applications reveals a field that is steadily advancing in depth, complexity, and specialization. The current section summarizes the primary overarching **trends** identified in the previous evaluation, offers a **comparison** with earlier reviews to highlight both converging and newly generated trends, and concludes with a discussion of **future directions** for MPC research in BEMS.

7.1. Trends Identification

One key trend concerns the increasing alignment between the **complexity of models and the sophistication of solvers**. Earlier MPC systems typically included white-box models and QP solvers for simplicity and interpretability [61,117]. However, as applications scale to multi-zone building models and integrate RES and other energy systems, gray- and black-box models are gaining popularity for their flexibility, often paired with heuristic solvers like GA or PSO [171,186]. This trend introduces trade-offs in solver tractability, prompting hybrid solutions—e.g., embedding linear ANNs in MILP [168] or combining surrogate models with metaheuristic search [179]. As is evident, future research will focus on co-designed model/solver frameworks able to balance fidelity, speed, and usability. **Black-box MPC methods are becoming more widespread**, especially in commercial buildings where HVAC control benefits from high prediction accuracy [169,174,175]. Advances in ML, particularly in ANN architectures—such as LSTMs—have improved forecasting performance [183,189]. However, it is evident that such models often lack transparency and generalizability, raising concerns in regulated or safety-critical environments [180,188]. Emerging strategies such as physically consistent deep learning [190] and explainable AI techniques may offer promising solutions to bridge this gap. Additionally, while ML is increasingly integrated into MPC frameworks, many studies still **lack mechanisms for adaptivity and robustness**. Few works evaluated controller performance under uncertainty, delays, or model drift [177,181]. Adaptive MPC and online learning remained underutilized, despite their potential to handle dynamic building conditions. This gap may be hindered by the integration of advanced mechanisms of control theory, considering real-time recalibration, uncertainty propagation, and resilience to unforeseen disruptions [166,189].

Another significant observation concerns the **high utilization of multi-objective MPC**, where energy efficiency is optimized alongside comfort, air quality, emissions, or user satisfaction [170,172,186]. This shift was reflected especially in cases of large buildings or district-level systems [173,188]. This trend, however, was not yet widely embraced in practice—with only 3 documented instances of multi-agent control across nearly 100 MPC reviewed applications. Such **limited decentralized and distributed MPC formulations** revealed a critical research gap, particularly given that distributed control is theoretically well suited for scalable, modular, and heterogeneous BEMS architectures.

Another persistent challenge depicted in the literature concerns the **absence of standardized benchmarks**. Many studies utilized unique case setups and evaluation metrics, making it difficult to compare results or assess progress at scale [170,179]. Open platforms like CityLearn offered a promising way forward, but the field still needs shared models, datasets, and KPIs across modeling types and climates to ensure reproducibility and comparability. Moreover, according to this evaluation, there is a growing effort to develop MPC systems where all parts—forecasting, control decisions, and real-time operation—work together as a single, well-connected process. Some recent studies showed how this may be achievable using adaptive ANN-based MPC [184], ML with uncertainty handling [117], or black-box MPC combined with explainability features [172]. Such examples highlighted that the best results come when all parts of the system are designed and optimized together—not separately.

As concerns the utilization of the different energy systems and equipment, MPC studies illustrated a shift from traditional HVAC-only control towards orchestrating integrated energy systems, including HPs, RES, ESS, and even EVs and lighting. In such cases, mixed-integer formulations—like MILP—are widely used to manage discrete operational modes, while energy flexibility and thermal inertia are increasingly leveraged for peak shaving and cost reduction. Moreover, control zoning has evolved **from simple single-zone configurations to multi-zone and large-scale implementations**, requiring hierarchical structures and scalable solvers. It seems that BEMS are gradually becoming perceived as modular energy subsystems, especially when coupled with localized RES and ESS.

Noticeably, most studies are conducted in simulation environments, particularly for black-box and especially RL-based MPC, while **real-world applications remain limited to simpler gray-box HVAC controllers**. The lack of real deployments for complex BEMS and RL strategies revealed a gap between research and practice, emphasizing the need for hybrid validation platforms and standardized benchmarking. Last but not least, the use of software tools was also diversifying: MATLAB remained widely used for classical control, while Python led in ML and RL applications. Simulation environments like EnergyPlus and Modelica supported high-fidelity co-simulation, often integrated via optimization platforms and middlewares such as LabView and BCTVE. Such trends underlined the transition toward flexible, interoperable platforms capable of supporting intelligent, data-driven MPC control solutions.

7.2. Comparison with Prior Reviews: Established and New Trends

A comparison with earlier surveys reveals that many of the trends identified in this review are consistent with established findings in the literature. Previous reviews have regularly emphasized MPC's capacity to reduce energy consumption and operating costs while preserving occupant comfort, though they have also highlighted the absence of standardized benchmarking frameworks across studies [46,49]. Similarly, our analysis confirms the importance of key design parameters—such as prediction horizon and sampling interval—influencing control performance. This aligns with observations by [48], who reported the use of day-ahead prediction horizons and sampling intervals ranging from 5 to 60 min. Uncertainty, particularly related to weather and occupancy, also remains a recurring challenge. Both [48,49] identified these factors as critical limitations, a conclusion further supported by the present review. Another point of convergence concerns computational burden. As noted in [47], approaches such as explicit MPC and move blocking have been adopted to reduce computational time—an issue that remains central even in more recent implementations.

At the same time, the current review identifies several emerging scientific trends that were not systematically addressed in earlier surveys. One prominent shift is the move from purely white-box modeling toward gray- and black-box approaches, with gray-box models increasingly favored for their balance between interpretability and modeling flexibility. This transition is accompanied by characteristic solver–model pairings: gray-box models are frequently solved using QP or MILP formulations, whereas black-box or ML-based approaches are often paired with metaheuristics or hybrid optimization frameworks. Another emerging direction is the growing adoption of multi-objective MPC strategies, where energy savings are optimized alongside additional performance metrics such as cost, emissions, comfort, and flexibility. This expansion reflects a broader evolution from the traditional energy–comfort trade-off to a more holistic understanding of building performance and sustainability. The review also highlights the limited uptake of distributed and multi-agent MPC schemes—despite their theoretical advantages in modular and scalable systems—with only three such implementations identified among nearly one hundred studies. In parallel, the scope of MPC has notably expanded beyond HVAC systems to encompass fully integrated energy systems, including RES, ESS, EVCS

DHW, and lighting. This trend reflects the increasing emphasis on grid-interactive and sector-coupled building designs.

Moreover, zoning and building typology are shown to significantly impact controller design and complexity. As the field moves from single-zone applications toward larger, multi-zone deployments, the need for hierarchical coordination becomes more pronounced. The review also offers insights into deployment environments and toolchains: simulation platforms such as EnergyPlus and Modelica remain dominant, while Python continues to gain prominence—particularly in machine learning and reinforcement-learning-based MPC frameworks. However, real-world deployment of advanced strategies remains limited. Altogether, these findings offer a statistically grounded view of current and emerging research directions in MPC for buildings—many of which were not captured in detail by earlier reviews.

7.3. Future Directions

The current review reveals a research landscape that, while rich in advances in modeling fidelity, optimization strategies, and predictive performance, still faces important challenges—particularly considering the reliance on centralized architectures, limited adaptability, and insufficient integration of occupant behavior. As BEMS continue to evolve into more dynamic, interconnected ecosystems, future research must rethink MPC not as a static controller, but as a flexible, modular, and learning-oriented framework capable of operating under uncertainty and continuous change. A key priority lies in the development of multi-agent MPC frameworks. Such control architectures are particularly well-suited for managing complex systems such as multi-zone building models, integrated energy systems, or networks of buildings. Despite their conceptual alignment with these use cases, they remained underrepresented in the MPC literature of the last decade. Future designs should embrace decentralized agents—each governing energy subsystems like HVAC, storage, or on-site generation—that coordinate through hierarchical or peer-to-peer communication schemes. To move forward, such agents need to handle asynchronous operations, partial system observability, and distributed negotiation, while maintaining overall system coherence. Federated control methods, which enable models to be trained locally and then aggregated, may present a promising solution for preserving privacy and scalability across large building portfolios.

Another pressing direction concerns the integration of forecasting and control into a single, co-optimized loop. In most existing implementations, forecasts were developed independently from the control logic, and often optimized for accuracy alone. Such separation may reduce overall system effectiveness. Future MPC frameworks should incorporate control-aware forecasting, where the predictive models are trained to optimize system-level outcomes like cost, comfort, or emissions. Emerging methods such as differentiable MPC approaches—where both neural networks and control policies are trained end-to-end—could align forecasting with control objectives, resulting in less conservative and more robust behavior, especially under volatile or uncertain conditions.

Hybrid control architectures that combine the strengths of physical modeling and data-driven learning also offer substantial promise. While purely black-box approaches are often prohibited by poor interpretability, and white-box methods struggle with generalization, combining the two could provide a robust middle ground. By integrating gray-box thermal models, black-box surrogates, and rule-based fallback mechanisms, potential hybrid frameworks may support more reliable and resilient real-world operation. In particular, for RL-based MPC—which remains largely confined to simulation—such hybrid schemes are critical to ensuring both safe exploration and meaningful policy interpretability.

The role of the occupant in MPC must also evolve. Rather than treating human presence and behavior as external disturbances, future systems should model those elements as integral, adaptive components of control. Behavioral preferences, usage patterns, and comfort thresholds can be inferred from sensor data—ranging from wearables to smart appliances—and used to inform personalized control strategies. Adaptive MPC systems should be capable of adjusting control actions over time, incorporating user feedback and evolving toward occupant-specific solutions. Techniques such as inverse RL could even allow controllers to infer user preferences implicitly, shifting the paradigm from optimizing around occupants to optimizing with them.

Moreover, as buildings increasingly engage in grid services and participate in energy markets, MPC systems must also be able to operate across multiple energy domains and regulatory contexts. The growing integration of RES, EVs, and bidirectional power flows calls for control strategies that are responsive not only to internal building demands but also to external signals. Future research should therefore develop MPC frameworks capable of optimizing flexibility in real time, factoring in time-varying tariffs, grid constraints, and market participation. Economic MPC schemes, extended with mechanisms like bilevel optimization or game-theoretic coordination, will likely be central to realizing this perspective.

Finally, the path to real-world deployment remains a critical bottleneck. While most research still occurs in simulation, practical implementation requires controllers that are lightweight, explainable, and operable on edge devices. To this end, there is a growing need for control schemes that are adequate to operate reliably with limited computational resources, adapt in real time, and be updated over-the-air without dependency on cloud infrastructure. Systems that can self-correct, handle failures gracefully, and integrate smoothly with existing building management tools will be essential for widespread adoption.

In summary, the future of MPC in building energy systems lies in rethinking its foundations: shifting from centralized, rigid implementations to intelligent, adaptive, and human-aware systems. These next-generation controllers must learn continuously, operate collaboratively, and balance performance with transparency and trust. This is not just an evolution of the technology—it is a fundamental redefinition of how we manage and interact with the built environment.

8. Conclusions

The current in-depth review of model MPC in BEMS illustrates how the field has grown in scope, technical complexity, and ambition. One of the most evident developments concerns the diversification of modeling strategies—from transparent white-box models grounded in physical laws to scalable, data-rich black-box systems. Each of these carries inherent trade-offs: while white-box MPC offer interpretability, it is harder to scale; black-box MPC, though flexible and powerful, often lacks transparency and reliability in unfamiliar settings. Gray-box MPC appears to offer the best of both worlds, but it remains underrepresented in field-deployed applications. Control strategies have also evolved significantly. The field has moved beyond conventional MPC formulations to include robust, stochastic, economic, and increasingly learning-augmented methods. Multi-objective controllers that consider cost, emissions, and demand response are becoming the norm, reflecting broader energy and policy priorities.

At the same time, data-driven approaches such as ML and RL are pushing MPC into more adaptive, model-free territory. However, such advances still struggle with explainability, transferability, and assurance of performance in closed-loop scenarios. The growing interdependence between the chosen model and the solver used—whether MILP, NLP, or heuristic—signals a shift toward holistic solver–model co-design. A persistent weakness across the literature is the inconsistency in how performance is evaluated. While energy and cost metrics dominate, many studies rely on outdated or overly simplistic baselines, and very few explore how MPC systems respond under uncertainty or in edge-case conditions. Most evaluations are still confined to simulations, with limited real-world deployment to validate theoretical gains.

In summary, the field is clearly moving toward more integrated, adaptive, and intelligent control frameworks. Future-ready MPC systems will not treat modeling, forecasting, and optimization as separate components, but as deeply intertwined elements in a dynamic control ecosystem. The fusion of physical modeling, data-driven prediction, multi-agent optimization, and explainability will be critical to scaling MPC from academic theory to a central pillar of smart, decarbonized, and user-centered buildings.

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Abbreviations

ANN	Artificial neural network
BES	Building energy systems
BEMS	Building energy management systems
CVRMSE	Coefficient of variation of the root mean square error
DHW	Domestic hot water
DP	Dynamic programming
DRL	Deep reinforcement learning
EVCS	Electric vehicle charging system
ESS	Energy storage system
FH	Forecast horizon
GA	Genetic algorithm
GBDT	Gradient boosting decision tree
HVAC	Heating ventilation and air-conditioning
IBEMS	Integrated building energy management systems
IPM	Interior point methods
LM	Levenberg–Marquardt algorithm
LP	Linear programming
LQT	Linear quadratic tracking
LSTM	Long short-term memory
MAE	Mean absolute error
MBE	Mean bias error
MDP	Markov decision process
MILP	Mixed-integer linear programming
MIQP	Mixed-integer quadratic programming

MINLP	Mixed-integer nonlinear programming
ML	Machine learning
MPC	Model predictive control
NARX	Nonlinear autoregressive with exogenous inputs
NLP	Nonlinear programming
PID	Proportional-integral-derivative
PSO	Particle swarm optimization
QP	Quadratic programming
RBC	Rule-based control
RF	Random forest
RL	Reinforcement learning
RMSE	Root mean square error
SAC	Soft actor–critic
SCIP	Solving constraint integer programs
SQP	Sequential quadratic programming
SVR	Support vector regression
TSS	Thermal solar system
TS	Time step
RES	Renewable energy systems
LS	Lighting system

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