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Model Predictive Control of Heating, Ventilation, and Air Conditioning (HVAC) Systems: A State-of-the-Art Review

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ABSTRACT

Due to the fast advancement of communication and information technology, intelligent buildings have garnered great interest. These buildings can forecast weather, ambient temperature, and sun irradiation and can modify heating, ventilation, and air conditioning (HVAC) operations appropriately, based on current and previous data. This change is intended to reduce HVAC system energy usage while maintaining an appropriate degree of thermal comfort and indoor air quality. Since its inception, model predictive control (MPC) has been one of the prospective solutions for HVAC management systems to reduce both costs and energy usage. Additionally, MPC is becoming increasingly practical as the processing capacity of building automation systems increases and a large quantity of monitored building data becomes available. MPC also provides the potential to improve the energy efficiency of HVAC systems via its capacity to consider limitations, to predict disruptions, and to factor in multiple competing goals such as interior thermal comfort and building energy consumption. Although substantial research has been conducted on MPC in building HVAC systems, there is a shortage of critical reviews and a lack of a comprehensive framework that formulates and defines the applications. This article provides a comprehensive state-of-the-art overview of MPC in HVAC systems. Detailed discussions of modeling approaches and optimization algorithms are included. Numerous design aspects such as prediction horizon, occupancy behavior, building type, and cost function, that impact MPC performance are discussed in detail. The technical characteristics, advantages, and disadvantages of various types of modeling software are discussed. The primary objective of this work is to highlight critical design characteristics for the MPC control scheme and to give improved suggestions for future research. Moreover, numerous prospective scenarios have been suggested that might provide future research direction.

1. Introduction

This section discusses the motivation for studying model predictive control (MPC) in heating, ventilation, and air conditioning (HVAC) systems. Next, a literature survey on previous review papers published in this field is conducted to clarify the research gaps and paper contributions.

1.1. Motivation for using predictive models for HVAC control

With the substantial rise in energy demand, energy conservation has become a priority around the globe. The building sector is a focus of increased attention because this sector consumes over 36% of final energy consumption worldwide [1]. Building services such as HVAC systems account for almost 40% of energy use in buildings (aside from water heating, refrigeration, and lighting) [2]. HVAC system inefficiency results in the disruption of occupant comfort, emission of greenhouse gases, and energy waste. Thus, HVAC systems

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are a source of underutilized, avoidable energy loss, making them a prime focus of energy efficient control method development and implementation. In recent years, computational advances in data processing, storage, and transmission have enabled the design and deployment of increasingly sophisticated control methods [3]. However, the energy efficiency of HVAC systems still remains a persistent challenge.

To address this problem, controllers have garnered considerable interest as potential options for improving the energy efficiency of buildings. As such, a variety of control strategies, ranging from simple to advanced controllers, have been proposed in previous literature (detailed literature survey will be presented in Section 2). Along with energy conservation, these control strategies should also provide a satisfactory level of indoor air quality (IAQ) and occupants' thermal comfort (OTC) [4]. However, energy conservation goals often clash with OTC and IAQ requirements, posing a problematic optimization issue. Of all the control algorithms in the field, MPC is capable of minimizing energy consumption while providing satisfactory levels of IAQ and OTC [5]. This is due to the fact that MPC can impose tight restrictions on decision variables based on OTC requirements or use multi-objective optimization algorithms that may concurrently evaluate energy and comfort goals [6]. As such, MPC control of the HVAC system has gained considerable attention among researchers in the past few years, as Fig. 1 suggests.

The numbers in Fig. 1 were obtained after a thorough exploration of search engines such as Elsevier Online Library, Google Scholar, Web of Science, IEEE digital, and a few publications like Wiley, Taylor & Francis, etc. We searched through peer-reviewed journals, technical bulletins, textbooks, and dissertations. The following keywords were used to compile the databases through an iterative process of research: "MPC in HVAC," "Control strategies in HVAC," "MPC in variable air volume," "PID versus MPC," and "occupancy-based control in HVAC." This research aims to provide standard terminology and taxonomy that will serve as a unifying framework for all engineering disciplines involved in the design and control of buildings.

1.2. Previous literature surveys, research gaps, and paper contribution

Table 1 includes a brief description of the previously published review papers on predictive-based control of HVAC. While these papers are of excellent quality, a current review paper focusing on the MPC of HVAC

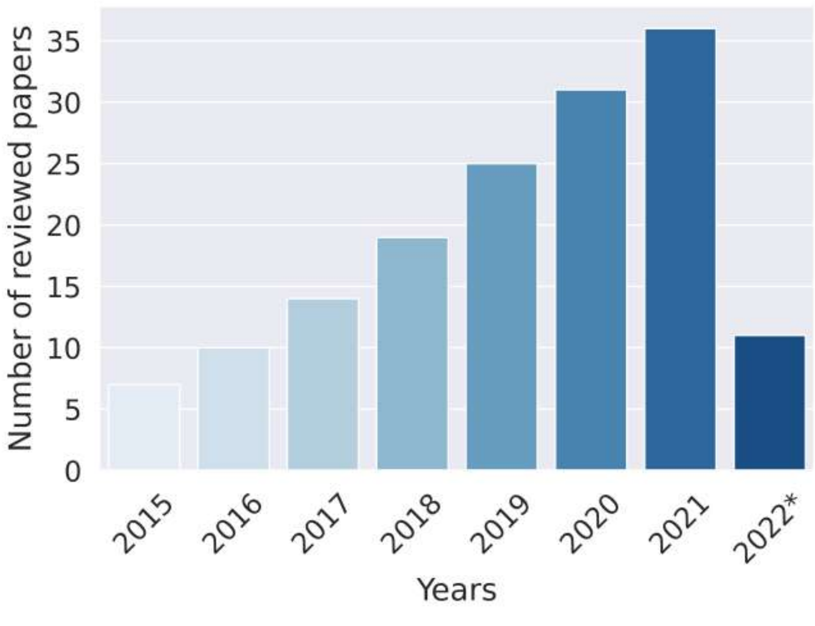

Figure 1: Number of published MPC-related papers during recent years.

Table 1
A summary of model predictive control studies suggested in the previous literature

Reference	Year	Description
[7]	2013	**Roger et al.** Advantage/disadvantage comparison of MPC vs other HVAC control strategies.
[8]	2014	**Zhe et al.** Review of optimum HVAC control methods, including set point value curves for individual components, control curves for independent units, and so on.
[9]	2014	**Abdul et al.** Reviewed the main HVAC control methods published in the literature at that time. Concentrated on the variables influencing HVAC control performance using a thorough literature survey.
[10]	2016	**Amin et al.** Provided an in-depth examination of occupancy-based MPC. Made a comparative analysis of model-free (data-driven) and physics-based MPC approaches.
[11]	2017	**Abdul et al.** A thorough study of the design of MPC systems using artificial neural networks. Focused on a real-world case study to design a supervisory MPC for residential buildings.
[12]	2018	**Gianluca et al.** Explored different MPC algorithms in HVAC system management. Highlighted the use of MPC to improve building energy efficiency. Provided a common MPC formulation framework for all technical disciplines engaged in the field.
[13]	2019	**Nishith et al.** Overviewed the benefits and drawbacks of using MPC in commercial HVAC systems. A decomposed MPC solution was introduced to decentralized MPC in a real-world case study.
[14]	2019	**Wooyoung et al.** The effects of thermal sensitivity and temperature setpoint resolution have been reviewed in multi-zone ventilation. Various multi-occupancy situations were overviewed with a focus on agent-based modeling.

systems remains a need. The following paragraphs elaborate more on the details and the gaps that are still unexplored by those review papers.

Some of these papers focused on examining a variety of simple HVAC management techniques without delving further into more complex control models. For example, publications [8, 9] concentrated on traditional building control approaches, excluding MPC approaches. When such review papers do discuss MPC, a wider picture of MPC variations is not provided–see references [10, 14] as examples. Reference [11] conducted a thorough study on the details associated with the design of MPC controllers using data-driven approaches; however, the study neither addressed the disadvantages of applying machine learning algorithms nor discussed other variations of MPC. In [12] different MPC architectures used in HVACs are represented and various MPC formulations are discussed, yet, the results of this research do not indicate which kind of MPC control is the most promising and cost/ energy efficient, or what quantifiable effects MPC's possess. This makes it difficult for other researchers to determine the best MPC design for a particular task and a specific building type. Reference [13] provided a comprehensive review, covering several topics related to MPC including disturbances, occupancy pattern modeling, thermal comfort, and uncertainty sources. These have been active study fields in recent years, as shown by the considerable number of articles published in this landscape. Thus, reference [13] did give a summary of previously published studies in this area, but largely ignore the methods' merits and weaknesses. Additionally, this article, which is the closest match to the present research, was published in 2019 and many investigations have been performed since and substantial body of research has been conducted, necessitating the need for a fresh review paper. This expanding tendency emphasizes the need of an up-to-date review paper examining the most current state-of-the-art procedures.

Nonetheless, extensive research on MPC variations and their application under various criteria had not been performed. A comprehensive overview of modeling approaches with their strengths and weaknesses, categorization of optimization methods, design parameters, and constraints used in MPC for HVACs had not yet been produced. This study distinguishes itself from previous publications by addressing these issues and providing a broader understanding of several facets of MPC operations. By incorporating more recent publications and providing a detailed picture of many factors related to MPC control, these gaps will be highlighted. The MPC scheme's application in building HVAC systems with a comprehensive examination of MPC variations and their application in a variety of circumstances are discussed. A broader perspective on the design of MPC components for efficient control actions is addressed exhaustively using sufficient prior material. The main objective is to use the findings of this exhaustive literature evaluation to examine the present research gaps in this subject and, as a consequence, to recommend future research initiatives. To do this, the examined articles are first classified into several groups based on their inclusion of different MPC strategies across time. Each category's articles are thoroughly assessed from a variety of viewpoints, including performance assessment methods, feature utilization in occupancy models, testbed kinds, and use of data. The evaluated articles are then summarized and examined from each angle in order to illuminate the research limitations across several aspects. This article will also assist in highlighting the present state of research on MPC and any flaws that have yet to be discovered. As a result, the key points and contributions of this paper can be summarized as:

- A comprehensive review of HVAC system control techniques is offered to provide a common language for different engineering disciplines interested in developing and designing control frameworks for HVACs (Section 2).
- A thorough comparative study was conducted to determine the MPC's performance in contrast to other control techniques (Section 3).
- A thorough examination of MPC variants and their applications under a variety of criterion enhances comprehensive reviews of modeling methodologies, including strengths and shortcomings, classifications of optimization methods and design parameters, as well as constraints employed in MPC for HVAC systems. Moreover, various aspects of MPC are explored, allowing the MPC issue to be conceptually articulated, facilitating the researchers' understanding (Section 4).
- A whole section is dedicated to the existing challenges and opportunities for MPC control of HVACs (Section 5).

This document will be formatted as follows: Section 2 offers an overview of different control strategies implemented in HVAC systems, along with a brief historical background and enumeration of advantages, and disadvantages of each control scheme. Performance comparison of MPC with other control strategies is conducted in Section 3. Section 4 discusses the MPC scheme's detailed theoretical formulations and further identifies several versions of the MPC scheme and illustrates them both theoretically and practically. The fourth section also highlights fundamental MPC concepts, such as optimizing objectives, modeling, restrictions, and design parameters necessary to represent the dynamics of the HVAC system. Section 5 discusses the difficulties and potential opportunities associated with implementing MPC to HVAC systems. Finally, Section 6 discusses the significant points extracted from this paper. This section will also serve as a guide for future researchers and anyone with a great interest in this topic and control technique.

2. HVAC Control Approaches

This section discusses different control strategies implemented in HVAC systems. To begin analyzing HVAC system control strategies, it is vital to create a differentiation between approaches since each is distinguished by specific characteristics and implementation implications. These approaches have been chosen to address recurrent issues in HVAC control, some are still persistent, including:

- The system's nonlinear dynamical behavior
- The abundance of variable and uncertain disturbances
- Time-varying setpoints
- Occupant-centric nature of ventilation
- Integration of modern technologies such as electrical and thermal storage
- The energy efficiency of HVAC systems

Table 2 presents some of the control methods implemented in HVAC systems over time. These control strategies can be divided into four groups. Fig. 2 shows the distribution of previous research according to the control strategy types and assessment techniques (simulation or field evaluation). As depicted, conventional control is the most prevalent control method used in prior research, accounting for over half of all investigations. It was followed by 31% of rule-based control. Observably, most of studies on optimum control have been simulation-based; few researchers have applied them to real-world testbeds. In contrast, fifty percent of research on rule-based analyzed actual case studies. While advanced control systems are still being developed, reactive and rule-based controls are commercially accessible for use in buildings. In reality, many commercial buildings currently use reactive tactics to regulate HVACs, therefore facilitating field assessment. In addition, advanced control often requires more processing capacity than building management systems presently possess. These considerations have made it more difficult to evaluate effective techniques experimentally. Consequently, there is a need to address this difficult issue and explore these systems when dealing with real situations.

The first category of HVAC control system is conventional controllers. Here, conventional control means those classical control strategies that are marked with use of methods with many decades of practical implementation, especially feedback control and PID (proportional, integral, and derivative) controllers. These classic models also contain manual control, feedback control, feed-forward control, On-Off, P (proportional), PI (proportional-integral), etc. Within this category, the simplest control method is the bang-bang controller, which utilizes a thermostat to give temperature feedback. A heating unit is activated when the temperature falls below a predetermined threshold in cold weather until the temperature reaches the preset temperature. A cooling unit is activated when the temperature exceeds a specified point in hot weather until the temperature returns to the setpoint. While bang-bang is a fundamental and easy-to-implement control technique, it is extremely energy inefficient and unsuccessful in tracking the setpoint temperature precisely due to frequent temperature overshoots [15].

These issues are partially resolved by incorporating PID controllers. For instance, On/Off or bang-bang controllers are quite frequent in older structures without digital control, but PID control loops are often used in more contemporary buildings with variable frequency motors. Reference [16] illustrates a simple example

Table 2
Different HVAC control strategies

Conventional control	Rule-based control	Hybrid, soft-computing control	Advanced control
Manual/On-Off	Gain Scheduling	Artificial Intelligence	MPC
Feedback	State-Space Multivariable	Fuzzy Logic	Robust MPC
Feed-forward	Transfer Function Method	Genetic Algorithm	Optimal Control
Bang-Bang	Self-Tuning Controller	Nonlinear Hybrid	Stochastic MPC
P, PI, PID	Nonlinear Controller	Data-Driven Control	Adaptive Control

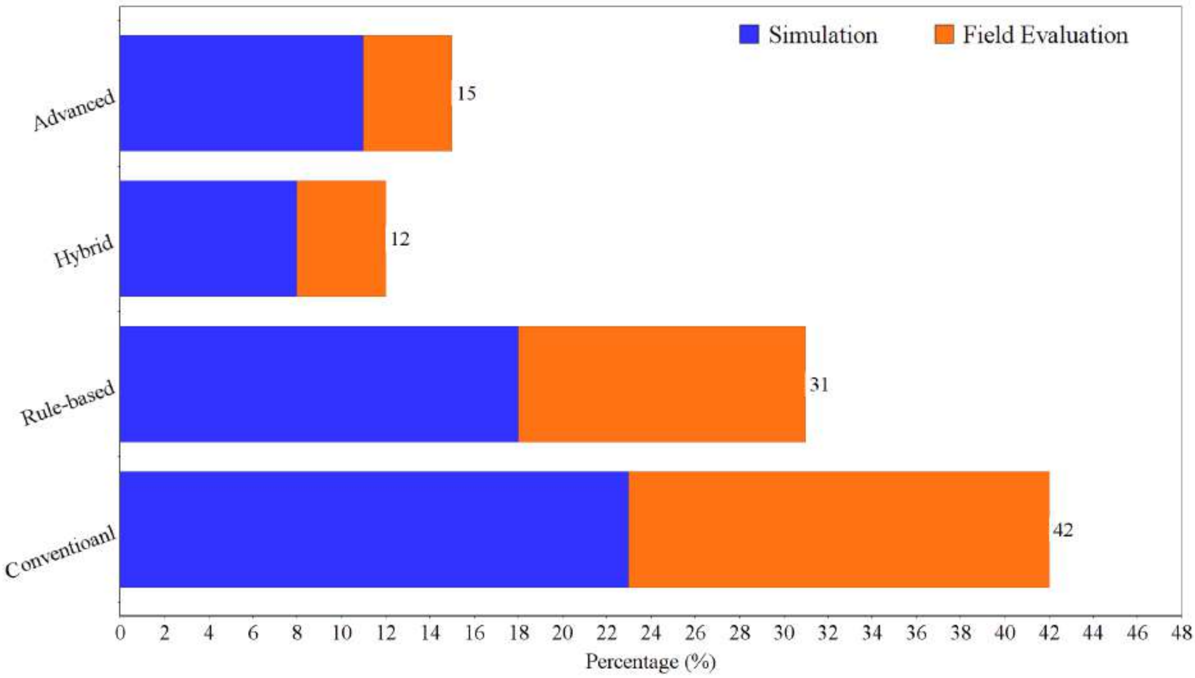

Figure 2: The distribution of previous studies according to control type and assessment methodologies.

of PID control by describing the construction of a portable device for automated tuning of PID regulators that may be utilized in HVACs. They provide a theoretical foundation for adjusting PID controllers and demonstrate how this may be accomplished using process data. The authors in [17] discuss the application of PID controllers to the management of the HVAC's in a large commercial building. PID control is used in conjunction with domain information to simulate human divisional control (by presenting various control types of situations); on-line tune PID parameters (based on accumulative error); and feed-forward control (based on outside conditions). The article [18] discusses in depth a classical control method based on PID controllers. The authors begin by describing the building and HVAC equipment and then develop a thermal model that encompasses all important thermal processes using a first-principles method. They get transfer functions using Laplace transformations. These formulations are used to simulate PID controllers in the heating mode for humidifiers and heating coils, and in the cooling mode for dehumidifiers and cooling coils. Ziegler-Nichol's tuning is used to tune PID controllers.

Although easy-to-build and reasonably inexpensive, PID controller is very laborious to tune and does not address the energy efficiency issue in buildings. Moreover, unsuccessfully adjusted PID controllers waste energy and have the potential to cause system instability. To account for the PID's inability to cope with the systems' real-time restrictions and nonlinear dynamics, rule-based controllers are frequently employed. In HVAC systems, rule-based control is a fashionable optimization method, in which a model is constructed using a set of "if-then-else" rules written by skilled property managers. To create a rule-based HVAC controller, a series of rules is created to operate each HVAC component independently for decoupling purposes. Adjustments are made to the setpoints of each PID loop of HVAC elements based on specified control rules. The order of principles is often determined by the designers' experience.

In this context, reference [19] created a rule-based control technique for regulating the flow of a solar water heating system equipped with energy storage, which resulted in a 43% reduction in running costs. The article [20] developed a rule-based control scheme for a heat pump combined with a thermal energy storage tank, which resulted in a 15% reduction in running costs. It seems that in HVAC systems with thermal storage tank, rule-based control is feasible and effective. Since rule-based techniques are often used to manage specific areas, there is typically no optimization at the building level, despite the presence of often complex local controllers. This implies the absence of a higher layer suitable for optimizing the set-point of each controller as an integrated system. This can be attributed both to the high degree of complexity needed for each rule-based controller and to the impossibility of generalizing their regulations at the building level.

The 1980s saw a shift in emphasis toward the development and deployment of intelligent approaches for building control systems. Using evolutionary algorithms, smart controllers might be properly tailored for controlling the many subsystems of modern buildings. To do this, learning-based systems derived from Artificial Intelligence (AI) techniques provide a novel approach to the energy management issue in comparison to traditional methods. AI-based control can cope with noisy or partial input as well as system nonlinearities. After training, it is capable of making predictions and subsequently controlling the HVAC system [21]. The most often utilized AI technique is Artificial Neural Networks (ANN), which have been widely employed in the prediction of buildings and HVAC management techniques [22, 23].

Additionally, fuzzy logic controllers may provide a solution by coupling and combining management of all the various HVAC system requirements and components. The article [24] illustrates a basic use of fuzzy logic in HVAC control. The authors employ a fuzzy controller to manage the operation of HVAC units in four rooms of a single building when there is insufficient energy to keep them all on. The fuzzy controller must ensure internal thermal comfort while avoiding situations in which the HVAC power demand exceeds the available power (peak-load reduction). The authors demonstrate their controller in a laboratory setting. A similar strategy is used in [25]. The authors use two fuzzy controllers: one analyzes the building and active energy customers to determine the quantity of available energy; the second allocates available energy to maintain a comfortable temperature in each zone.

Paper [26] discusses Fuzzy Logic. The authors begin by providing a thorough theoretical explanation to Fuzzy Logic Controllers (FLCs): Knowledge Base, Interface System, Fuzzification Interface, and Defuzzification Interface. The capability of FLC to handle multi-criteria control schemes has been identified as one of its most critical qualities. The second section of the research discusses genetic tuning of FLC, which is likewise extensively described. After that, the authors focus on their own contribution: a Weighted Multi-Criterion Steady-State Genetic Algorithm (WMCSSGA) for FLC tuning. This technique is then used in two distinct real-world test locations, one of which is run in two distinct seasons: summer and mid-season. The experiment's findings are examined, with an emphasis on energy efficiency improvements and system stability.

Other than Fuzzy approach, Genetic algorithm is an optimization approach for enhancing the parameters of HVAC control systems. The use of Genetic algorithm to tune the settings of classical controllers [27] and Fuzzy Logic controllers [28] has been widely investigated. Additionally, genetic algorithms are used to find the important thermal parameters of a zone model using data [29] and to improve ANN models for HVAC system control [30]. Furthermore, Genetic algorithms have been applied to optimize energy usage, renewable energy production, and energy storage coordination [31]. The article [32] discusses the use of Fuzzy Logic

Controllers in conjunction with Genetic algorithms to create what the authors refer to as Evolutionary Fuzzy Rule-Based models. The list of rules is constructed directly from the data, without reference to any prior model knowledge. The authors concentrate their efforts on limiting the computational burden (and complexity) to a manageable level via the use of rule indices. Additionally, this strategy enables physical interpretation of the model. The proposed technique is validated using a model of a natural-gas boiler's control system. Another application of Fuzzy and Genetic algorithms is described in article [33], in which Fuzzy logic is used to control water and steam valves. The authors begin by providing a thorough model of valves and an Air Handling Unit (AHU), after which they develop a multi-criteria controller for humidity and temperature. Because this controller is also capable of self-tuning in response to changing circumstances, it is referred to as an Adaptive Fuzzy Controller. They demonstrate how to utilize Genetic algorithm to change Fuzzy concept and derive the lowest feasible error. Additionally, the results indicate an increase in responsiveness (settling and rise times). Despite their many benefits, these control algorithms are not ideal for efficient control of smart buildings, IAQ monitoring, or greater energy savings due to their emphasis on interior environment conditioning without considering a prediction horizon for control trajectory.

In recent years, a growing number of studies examining the potential presented by the deployment of classical control principles-based procedures have been published. These studies have established that Model Predictive Control (MPC) algorithms are an effective way off increasing the energy efficiency of buildings. MPC is a well-established technique for HVAC control that has lately garnered significant interest from subject-matter experts to solve the aforementioned problems. Also, MPC enables the use of energy storage capacities and the optimization of on-site renewable energy output. MPC is capable of anticipating the energy demands of the building and optimizing its thermal behavior based on set control objectives by using both predicted future disruptions (e.g., weather, internal gains, etc.) and provided requirements such as occupant comfort. Constraints are immediately interjected into the optimization problem at each sample phase. Until the last decade, the MPC framework had an uphill battle to achieve practical implementation, owing to the framework's high processing requirements for huge optimization tasks. MPC is now increasingly being used in many sorts of buildings and with a variety of energy systems as graphics processing units, processors, and cloud computing are developed and available computational power exponentially increases. Only a few years ago, an evaluation of modern building control systems classified predictive optimum controllers, such as MPC, as marginal methods. Since that time, the use of MPC in buildings has garnered growing interest. MPC implementation is primarily possible because of increased affordability of hardware, increased data accessibility, and advancements in information technology which enable the gathering, storage, and analysis of massive amounts of building-related data. As a result, if the data collected is appropriately analyzed using data-driven techniques, it may give critical information about the real performance of the building and the facility's energy consumption. As a result, analyzing this observed data may provide an extremely efficient means of converting the extracted information into practical energy savings and active demand solutions for increasing the efficiency of buildings and HVAC systems. In turn, much effort will be expended on developing more complex and predictive control approaches to maximize the energy efficiency of buildings. Consequently, the implementation of model-based and prediction-based control approaches capable of optimizing trade-offs between competing goals is extremely desired.

MPC combines numerical optimization concepts and feedback control and is composed of an optimizer solver, a plant model, and a prediction horizon to determine a process's control trajectory. MPC has a variety of technological advantages and characteristics that make it a popular option for control techniques in building systems. For example, MPC is capable of optimizing several parameters such as temperature set point, valve position, and flow rate set point. Additionally, it incorporates feed forward control to adapt observable disruptions such as climate projections, occupancy rate, and so on [34]. MPC features easy-to-implement control rules, which means that given optimization problems are solved using a variety of approaches such as linear, quadratic, and dynamic programming, as well as genetic algorithms and particle swarm optimization.

Therefore, the optimization strategies utilized will vary according to the optimization problem's nature. This leads to various MPC architectures to solve a building control problem that must be chosen according to the kind of prediction model established. As a result, there is a need to discuss different variants of MPC, mathematical formulation, and their applications. It is worthy to mention that due to the computing effort needed by MPC, its deployment has previously been limited to buildings in the design phase, since only modern HVAC systems are equipped with hardware capable of executing the control algorithm. As the speed of available computer hardware has grown dramatically and new, quicker algorithms have been created, it is now viable to apply MPC in older HVAC systems. Moreover, while it is preferable to consider using MPC at the design/planning phase, it is also viable to replace the HVAC system's present control mechanism.

3. Comparison of MPC with Other Control Approaches

MPC forecasts the future states of a system using a system model and provides a control scheme that minimizes a specified cost function across the prediction horizon in the presence of restrictions and disturbances. At each sampling interval, the first component of the computed decision variables is fed to the system's input, with the remainder of the variables being discarded. The whole procedure is repeated in subsequent sampling intervals. This technique could be implemented utilizing constraints for multiple-input, multiple-output (MIMO) systems and has been used to build energy controls with different objective targets. These objectives may be expressed as tracking inaccuracy, control effort, energy cost, demand cost, power consumption, or a combination of these elements. Constraints may be imposed on the actuators' rate and range limits, as well as on the manipulated and controlled variables (e.g., lower and upper zone temperatures, damper placement range, supply airflow rate restrictions, and damper speed limits). Internal and external disturbances such as tenant activity, weather, and equipment usage are also modeled, and their expected impacts on the system are utilized to compute the optimal control parameters. This work results in a controller that is both resistant to time-varying disturbances and system characteristics and firmly controls the process within the specified constraints.

To assess the performance of a control algorithm, the comparative measures listed below are often used:

- Capacity to transfer peak loads
- Cost, resource, and energy savings
- Reduction in offset error or enhancement of steady state responsiveness
- Improved transient responsiveness such as settling, rising, and peak time
- Ability to keep decision variables within the predetermined limits
- HVAC runtime
- Improved regulation and reduced variation from set-points
- Stability in the face of disruptions and changes in operational circumstances
- Enhancement of IAQ and thermal comfort
- Reduced computational burden

The majority of researchers compare their proposed controller's performance to that of others using one or two of the performance measures listed above. The frequency of application of various performance criteria for evaluating HVAC control is shown in Fig. 3. As depicted, energy conservation is the most often used performance metric in prior research. However, focusing only on energy savings might result in an underestimation of MPC advantages, particularly when compared to reactive control performance. This is because reactive strategies often reduces energy usage at the price of OCT, while MPC can enhance OCT via preconditioning the building. This preconditioning may result in increased energy consumption, and if only energy savings are considered, reactive control can outperform MPC if the advantages of OCT are overlooked. As a result, it is highly advised that while assessing the efficacy of predictive control systems, thermal comfort conditions be taken into account.

Utilizing the aforementioned performance criteria, MPC is proven to beat the majority of control approaches for HVAC systems. Numerous academics demonstrate the importance and benefits of MPC techniques via simulation and experimental investigations. As an example, the authors in [35] used MPC to manage the damper position and zone temperature in a simulated variable air volume (VAV) system. In comparison to a PI controller, the MPC controller demonstrated improved settling time, overshoot, and rise time, and was more resilient in the face of pressure disturbances from air ducts. The PI controller provided a slow reaction while regulating a low-flow-rate set point, requiring more time to achieve the set point. When the set point was set to a high flowrate, the PI controller reacted very aggressively, resulting in excessive overshoots over the set point. In comparison, the MPC-based method generated consistent answers in both circumstances and resulted in a shorter settling time and less overshoot. When zone temperature regulation was evaluated for low and high cooling loads, the PI controller maintained the process exactly at the set point, while the MPC maintained the process within a reasonable range around the set point. However, the PI controller exerted a far greater amount of control effort than the MPC controller. By examining the control signals produced by the PI and MPC controllers, it was discovered that the PI controller signal fluctuated much more at low cooling loads and oscillated at high cooling loads, necessitating re-tuning. In comparison, MPC generated a much smoother control signal in both high and low cooling load settings. Additionally, HVAC runtime has been infrequently used by academics to evaluate the effectiveness of control methods. This is because there is not necessarily a correlation between HVAC run time and energy savings, and using HVAC run time as a performance metric might result in system performance overestimation. As a consequence, conserving energy rather than increasing HVAC run duration is more advised for more dependable outcomes.

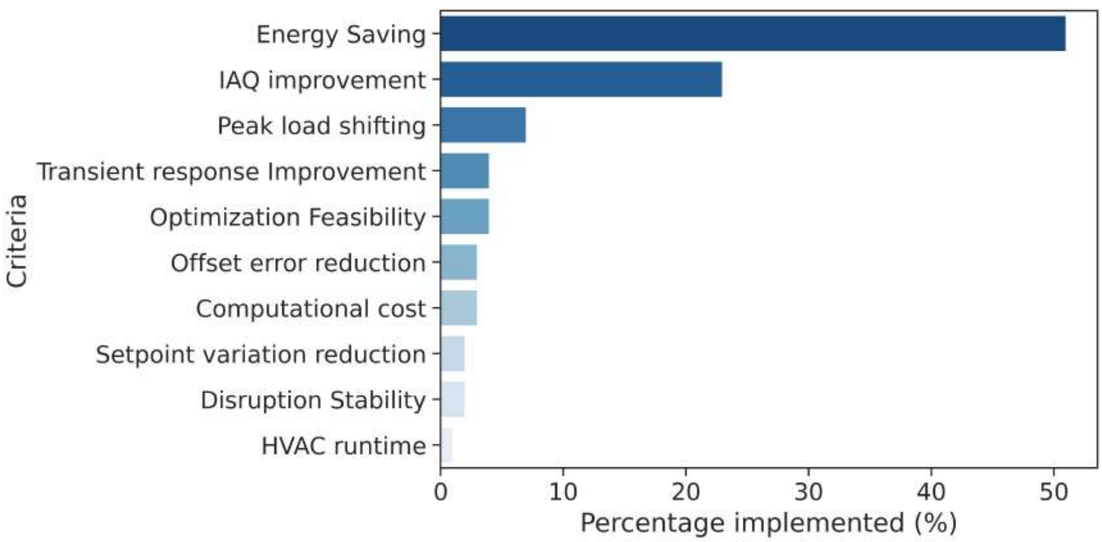

Figure 3: The frequency with which various performance criteria were used to evaluate the benefits of HVAC control systems in the previous literature.

A simulation investigation of zone temperature control was undertaken by Ref [36] employing decentralized MPC, distributed MPC, and centralized MPC. When there are coupling effects between adjacent places, all the setpoints were professionally managed utilizing distributed and centralized MPC. The PI controllers used a decentralized structure since the impacts of zone coupling had not been considered. In a multi-zone scenario, each PI controller independently controlled the zone temperature without sharing any information with the surrounding controllers. The behavior of the multi-zone decentralized MPC controllers was similar to that of the PI controller. The distributed and centralized MPC controllers, on the other hand, adjusted for nearby spatial coupling effects by formulating predictions and sending control choices to the neighboring controllers. Decentralized MPC was able to decrease energy consumption by around 6% when compared to the PI controller, while distributed and centralized MPC were able to achieve an extra 37% gain in thermal comfort and a 14% reduction in energy consumption.

When utilized to manage the ventilation and temperature of multiple zones in [37], the MPC approach was able to maintain temperature restrictions and provide acceptable ventilation depending on the zone's habitation. However, the Proportional controller struggled to uphold temperatures within the desired thermal comfort range on a continuous basis., resulting in inadequate ventilation as occupancy grew.

The supply water temperature of a heating system was calculated using MPC to get the required zone temperature, and the results are comparable with that of a Simulink model in [38]. The MPC ensured that the room temperature always remained within the target range by using forecast and allowing for the building's idle time. However, since the precise solution approach did not include weather predictions, it was unable to keep the ambient temperature at the specified value throughout all moments.

MPC was employed to shift electricity loads while controlling zone temperature in [39]. Peak demands were relocated, and the on-peak electricity profile was smoothed using the MPC approach. MPC saved more than twice as much (25%) as the step-up (24%) and sequential (17%) techniques.

MPC outperformed such traditional control systems as constant proportion control, chiller priority control, and storage priority control when used for discharging and charging an ice storage system, as stated in [40]. In study [41], supervisory MPC was utilized to develop the best precooling profile, the optimum spatial temperature set points, and the optimum thermal storage discharging and charging configuration. When compared to a standard chiller control scheme that does not include chiller priority management or thermal storage, MPC resulted in additional efficiency improvements of 16% and 26%, respectively. In Ref. [42], energy consumption of the heat pump was lowered by using a supervisory MPC to compute the optimum sequence of set points for a water tank system.

MPC-based and PID-based controlling of dry bulb temperature were simulated via Matlab for an off-coil air from the AHU in [43]. In comparison to the PID controller, MPC exhibited quicker settling time and reduced overshoot. The controller was deployed on a pilot HVAC system of a laboratory. Additionally, the developed controller demonstrated greater robustness and tracking performance when compared to the PID controller.

MIMO MPC is utilized in [44] to regulate the temperature of several zones that used an electronic expansion valve. Additionally, the MPC is used to adjust the evaporation pressure and temperature through compressor speed control and water flow valve. Local and state level PI controllers also are developed on the aforementioned processes for comparative reasons. The MPC controller exceeded the PI controllers in many ways, including superior management of evaporator pressure and superheat temperature. By incorporating supervisory MPC into the system, the coefficient of performance (COP) increased by 10%, resulting in significantly increased efficiency.

In [45], an industrial facility is chosen as a testbed to regulate the temperature of the supply air using feedback linearization and MPC. The MPC controller operated well, exhibiting excellent trajectory tracking. The MPC might include dead time in the process and utilize future values of the reference signal. As a result, the MPC controller displayed reduced overshoot, faster settling time, and shorter reaction time when compared to a controller with predefined error dynamics.

The MPC's performance is compared to that of a finely tuned weather compensated controller that also employed weather forecasting in a large university building in [46], and to that of the heating curve approach in [47]. In both cases, the MPC used 30% less energy while providing the same degree of thermal comfort. Due to the building's considerable thermal capacity, MPC heated the building in advance to more precisely match the reference trajectory. The weather-compensated controller provided water to the radiant ceiling heating system at a much higher temperature than the MPC controller, which resulted in increased energy usage. The heating curve approach warmed the building's concrete overnight and then shut off the heating in the morning. Additionally, the MPC prepared the building at night but did not turn off the heating during the day, resulting in a large peak energy decrease.

In [48], an MPC and a fuzzy controller were used to manage the humidity and zone temperature of a thermal tank in a school lab. In comparison to the Fuzzy controller, the MPC displayed greater performance: it reduced settling time by 20% steady-state error by 300% and for humidity and temperature by 90%.

In [49], on/off control is compared to a data-driven MPC utilizing a single heat pump air conditioning system placed in a school lab. MPC based on learning lowered energy usage by 25%–65% when compared to on/off control. Energy savings decreased when occupancy and outside air temperature rose, putting a greater thermal demand on the air conditioner.

In summary, both experimental and simulation studies indicate that using MPC for HVAC system control has a number of benefits. The subsequent sections discuss the MPC variants, components, and implementation practices.

4. Different Types of Model Predictive Control

This section offers a comprehensive overview of MPC variations and their relevance in a variety of scenarios. MPC is a relatively recent control technique introduced that arose in the late 1980s for process control in the chemical industry. MPC methodologies have been applied to building energy controls with the main purpose of minimizing energy consumption and maximizing utility time. Due to the combination of multiple optimum finding methods, MPC exhibits a variety of characteristics that may be classified as follows:

- Multiple variables, such as flow rate or temperature set point and valve position, can readily be handled via MPC control.
- MPC uses feed forward control to correct for quantifiable disruptions such as weather forecasts, occupancy rate, and etc.
- MPC offers an easy-to-implement control-law, i.e., a stated optimization problem, for which a variety of problem-solving approaches such as linear programming, quadratic programming, genetic algorithms, particle swarm optimization, and dynamic programming may be applied.
- MPC can minimize the objective function when well-defined restrictions are applied.

The optimal control actions necessary to meet an objective function are determined by solving an optimization model at each stage of the control process. The optimization objective and constraints are expressed as a generic form in (1)–(4).

$$\text{Objective : min} \sum_{t=0}^{k=T-1} f(\mathbf{x}_t, \mathbf{u}_t, \mathbf{d}_t) \tag{1}$$

$$\text{Subject} \quad \text{to} : x_t = a(\mathbf{x}_{t-1}, \mathbf{u}_{t-1}, \mathbf{d}_{t-1}); \quad \forall t \in \{1, 2, ..., T\} \tag{2}$$

$$x_0 = x \tag{3}$$

$$h_m(\mathbf{x}_t, \mathbf{u}_t, \mathbf{d}_{t-1}) \leq 0; \quad \forall t \in \{1, 2, ..., T\}, \forall m \in \{1, 2, ..., M\} \tag{4}$$

where the first equation represents the objective that consists of a function of input state vector $\mathbf{x}$, control input vector $\mathbf{u}$, and disturbance input vector $\mathbf{d}$. t signifies each time step in a prediction horizon of T steps. a is a function that updates the state variables. The behavior of the system is modeled using this function with starting states derived from observations (x_0), and projected disruptions. h is the function that represents the physical constraint m and M shows the total number of constraints. MPC scheme calculates the optimal control decision variables at each time step by solving this optimization model for the given prediction and control horizons, as shown in Fig. 4. The optimization is computed for a certain period that is called a prediction horizon. Next, the first or a subset of the calculated decision variables are regarded as inputs and the rest of variables are discarded. This procedure is repeated for each subsequent step in order to determine the optimal control signal. It is worth noting that when disturbances ($\mathbf{d}$) are included in the model, a conventional MPC model becomes a Robust MPC or a Stochastic MPC, as discussed in the following subsections.

4.1. Objective Function, Constraint, and Mathematical Formulation

Depending on the problem at hand, targeted goal for objective function, constraints, and modeling, the MPC control scheme will include different forms and variations. There are numerous types of MPC variants: stochastic MPC, robust MPC, adaptive MPC, distributed MPC, and hybrid MPC. Objective functions such as overall system efficiency, total building energy consumption, building-related greenhouse gas emissions, operation cost, interior temperature set-point, electricity cost, and occupant thermal comfort can be found in previous studies. For instance, in [50], total cost was employed as objective functions along with greenhouse gas emissions. The goal function in [51] was thermal energy intake and zone temperature control when occupancy level is fluctuating. In reference [52], the goal function was calculated using the Predicted Mean Vote (PMV) index. The results showed that considering PMV in conjunction with the control signal can result in improved performance. On the other hand, the authors in [53] indicated that both relative humidity

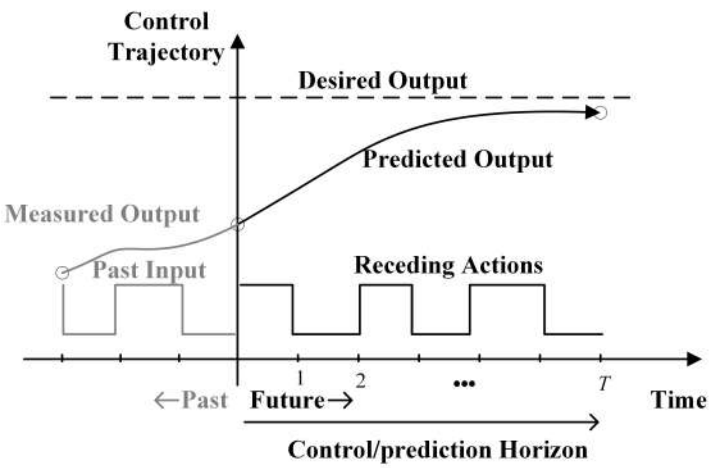

Figure 4: MPC control scheme.

Table 3
Objective functions and mathematical models used in MPC literature

Reference	Objective Function					Mathematical Modeling				Savings
	Energy Consumption	Utility Cost	Thermal Comfort	CO2 Emission	Temperature Error	Linear	L2 Norm	Quadratic	Non-linear	
[51]	✓			✓					✓	20%
[54]		✓		✓				✓		20%-32%
[52]		✓	PMV					✓		12.5%
[55]			PMV		✓		✓			-
[53]	✓		✓					✓		-
[56]	✓				✓				✓	27%
[57]	✓					✓			✓	24%
[58]	✓								✓	40%
[59]	✓					✓	✓			-
[49]	✓				✓			✓		50%
[60]		✓							✓	45%
[61]	✓							✓		44%
[62]	✓					✓				32%
[63]	✓								✓	24%
[64]	✓									55%
[65]	✓									-
[66]										31%
[67]	✓								✓	12%
[68]		✓								-
[69]								✓		-
[70]	✓								✓	25%
[71]	✓		PMV						✓	12%
[72]		✓	PPD						✓	17%
[73]		✓	PPD						✓	56%
[74]		✓			✓			✓		-
[75]		✓				✓				-
[76]		✓				✓				-

and zone temperature deviation from set-point, as well as total energy demand, may be utilized as objectives for maintaining zone comfort while minimizing energy consumption via psychrometric charts. The following table highlights the target functions discussed in several articles on building temperature control (Table 3).

Different mathematical models are obtained when MPC is utilized. The variation in mathematical models occure because of the diversity in buildings, modeling approaches, equipment characteristics, and different assumptions being made during the process. These mathematical models can be categorized into linear [59, 62, 75], L2-Norm [55, 59], quadratic [49, 52–54, 69], and non-linear [51, 53, 56, 57] forms. For a variety of real-world MPC problems, non-linear programming occurs in mathematical modelling. On the other hand, numerous MPC problems can be expressed as quadratic programming (QP) problems with a quadratic objective function and a linear collection of inequality and equality constraints. QP with linear constraints is essentially an extension of linear programming with a quadratic cost function. As such, it encompasses all LP difficulties including those encountered in planning and scheduling. Additionally, QP is known to be NP-hard, which implies that some of the most intriguing issues in combinatorial optimization may be presented in a QP framework. Although simple to solve, QP and linear programming suffer from collinearity and robustness. To solve these issues, a second order regularization term is usually added to the objective function; this is called L2-Norm.

Human thermal comfort is a critical constraint in the building climate control optimization issue. Thermal comfort in buildings is difficult to define because of the complicated dynamic of human beings. There are two primary techniques for incorporating this constraint into the problem: projected mean vote (PMV), which was first introduced by Fanger [77], and Predicted Percentage of Dissatisfied (PPD) which was pioneered by Becker [78]. PPD may be defined as the proportion of individuals that are dissatisfied with a certain PMV number. PMV and PPD might well be utilized as both the objective function and constraint in the optimization problem. To optimize occupant comfort and energy consumption simultaneously, [79] employed a data-driven logistic comfort model as a constraint on a deterministic and stochastic MPC. Utilizing MPC in conjunction with a PMV and PPD (in both constraint and objective function forms) is computationally costly. As a result, linearization of PPD and PMV formulas are adopted to reduce the complexity of the optimization [80].

Among the primary constraints on optimization issues are actuators and physical restrictions. The upper and lower limits for most of these functions are linear. A second critical constraint is the dynamical system that forecasts future states. In the majority of building control design scenarios, this constraint is nonlinear. Another intriguing component is stochastic constraints, which associate a probability to different scenarios of an uncertain event occurring in the MPC problem. Due to the fact that this kind of constraint renders the issue nondeterministic, it is often substituted with a deterministic constraint. There are a few additional potential constraints that are involved in MPC problems. For instance, the authors of ref [81] employed equipment efficiency as a constraint on total efficiency. Reference [82] took operational length into account, since some nations impose limitations on HVAC operating hours.

4.2. Stable and Robust MPC

The robustness of MPC to model uncertainty and noise has long been a source of debate among academics. A control system is said to be robust if it maintains stability and performs to standards throughout a class of noise signals, an interval of model revisions, and an interval of uncertainty ranges [83]. To be meaningful, a statement on the robustness of a certain control mechanism must relate to both specific stability and performance needs as well as a given uncertainty range.

Although an extensive theory for robust control of linear systems has been created, relatively little is known about robust control of linear systems with restrictions. This sort of issue has been addressed recently within the framework of MPC [84, 85]. Within the HVAC realm, MPC uses the plant's model to forecast future states of the system. Additionally, MPC is feedback controlled and adaptive. These characteristics make MPC an attractive choice for challenges with performance measurements and strict limitations. However, model uncertainty and connected subsystems cast considerable doubt on the reliability and scalability of this technique when applied to HVAC. The joint presence of uncertainty and physical constraints raises severe concerns about robustness [86]. Accurate modeling of buildings and HVAC systems is challenging because of model discrepancy or disruption causes. Common exogenous disturbance elements include cooling loads, sun irradiation, external temperature, and occupancy level [87]. Thus, uncertainties provide a challenge for the MPC control strategy, resulting in suboptimal accuracy. The issues may be resolved by the development of a robust MPC system. Robust MPC is an abridged form of nominal MPC that assures that all feasible uncertainty sequences satisfy the state control criteria. In this case, uncertainty is supposed to be constrained for robust MPC formulation.

We have not defined the stability restrictions in the MPC formulation (1-d). The following section discusses some of the most often used strategies in the literature for enforcing stability. These strategies are classified into two broad categories. The first employs a Lyapunov function at each time t during the optimization process [88]. The second presupposes explicitly that the state x(t) shrinks in some norm [89].

- End Terminal Constraint: Pioneered by Kwon [90], a stability constraint is added to the MPC formulation as follows:

$$x(t + T|t) = 0 \quad (5)$$

This converts the sequence of optimized decision variables and related constraints to a Lyapunov function at time $(t + 1)$. The primary disadvantage of applying terminal restrictions is that the control effort needed to direct the state back to the origin may be substantial, particularly for a small T, making feasibility more crucial. The closed-loop domain of attraction is confined to the set of beginning states x_0 that can be steered to zero in T steps while fulfilling (4), which may be much less than the set of initial states steerable to the origin in any number of steps. Additionally, performance may be harmed as a result of the artificial terminal limitation. A variant on the terminal constraint concept has been presented in [91]: Only the unstable modes are constrained to zero at the horizon's end. This alleviates some of the previously noted issues.

- Infinite Receding Horizon: The authors in [92] demonstrated that based on Lyapunov function, no stability requirement is necessary for the stable systems if $T = \infty$.
- Terminal Weighting Matrix: Reference [93] established that by selecting a terminal weighting matrix in (1) as the solution to a Riccati inequality [94], stability may be assured without the inclusion of any additional stability restrictions.

Several scholars have conducted research on the Robust MPC scheme and its applications. Nagpal et al. [95] used Robust MPC to manage the temperature of a building in the face of parametric uncertainty. This control algorithm proved effective in maintaining the target interior temperature range for the building even in the face of significant disturbance elements. To verify the outcomes of this control technique, numerical and simulation tests were conducted. Deng et al. [96] used adaptive Robust MPC to enhance building models and deal with disturbance uncertainty. This implementation resulted in a variance of energy savings of around 16%–21% as compared to the thermostat, despite an increase in disturbances from 10% to 50%. On the other hand, MPC without adaptive modeling and robust optimization achieves around 19% energy savings as the degree of uncertainty grows, but at the these saving are cost of thermal comfort. As a consequence, their findings further demonstrate that modeling a resilient optimization is utilized to avoid indoor conditions from breaking restrictions as a result of model inaccuracies and uncertainty. Reference [97] applied the Robust MPC scheme to variable air volume for zonal temperature control and demonstrated that the Robust MPC scheme was capable of enhancing robustness without requiring significant user intervention and was capable of effectively dealing with uncertainty factors such as disturbance factors and cooling load variability. The authors in [98] used a hybrid control strategy with full and minimum order observers to estimate interior temperature and humidity. They examined the influence of model uncertainty on the performance and control inputs of AHUs. Wang et al. [99] used the Robust MPC algorithm to manage the temperature of an air-conditioning system. When compared to PI controller, the findings demonstrated that Robust MPC leads to reliable and robust control while retaining appropriate thermal comfort. In [100], an off-line Robust MPC strategy is developed for efficient temperature control of a VAV. Through simulation findings, the authors concluded that the proposed Robust MPC system ensures needed robustness without being too conservative or considerably increasing the complexity of the calculation.

4.3. Stochastic MPC

In Robust MPC, the control sequence of state x is often obtained by solving the optimization model subject to all possible disturbance sequences while considering the worst-case scenario; however, in stochastic MPC this requirement turns to the minimization of an expected cost with respect to disturbance sequences. MPC requires prediction of the system's states and inputs in order to generate control actions. All of these forecasts and models imply uncertainty in the system. Reference [101] examined the influence of several sources of uncertainty on MPC performance by simulating a building using EnergyPlus. This research demonstrates that the most significant influence on MPC performance is caused by discrepancies in occupancy measurement and model uncertainty. This research demonstrates that mismatches in plant models may alter energy usage by up to 40% and occupancy fluctuations can alter energy consumption by up to 30%. Outside temperature and solar load measurement errors, on the other hand, have a negligible influence on MPC performance. Even with such errors, it has been shown that MPC controllers may save between 13 and 40% of energy when compared to traditional controllers.

MPC performance is impacted by building modeling, since the energy consumption in the building model may differ from actual energy consumption [102]. It can be shown that mismatching internal heat models may have an effect on MPC's thermal energy storage performance [103]. MPC needs future data on the majority of system and environment conditions, such as energy prices, outdoor and indoor temperatures, and occupancy levels. Because the majority of these projected data exhibit probabilistic behavior, it is critical to use stochastic MPC [104]. In [105], a Markov chain model was utilized to anticipate the behavior of Stochastic MPC, resulting in a 40% energy savings over a PID controller. However, Markov chain model enhanced the computational burden. In [106], an experimental assessment of Stochastic MPC with occupancy and weather predictions was conducted on a campus building. This research estimates that this controller can save between 6% and 25% of energy. The authors of [107] proposed a probabilistic-based MPC using weather forecasting as a stochastic variable. The outcome of this study indicates that stochastic MPC can outperform deterministic MPC by a significant margin. According to another study [108], Stochastic MPC results in at least 3% greater energy savings compared to a standard MPC when weather prediction is used.

4.4. Distributed MPC

The size of a building's model may expand rapidly in proportion to the number of rooms, resulting in a costly computing effort for MPC. Decentralized MPC offers a solution by decoupling the building dynamic into numerous discrete smaller equations that may be solved independently. In [99], a distributed MPC with occupancy and weather prediction was designed using a sequential quadratic program (SQP) and dual decomposition. [109] discusses how distributed MPC may be used to govern energy allocation amongst agents (rooms) in a system that incorporates renewable energy sources. The findings demonstrate that decentralized model predictive control (DMPC) may provide near-optimal solutions with little computing effort. Reference [88] simulates a distributed controller using a network of MPC controllers. Each MPC gets access to the average temperature of the neighboring zone. Dynamic programming was employed in this work to provide an analytical solution to distributed challenges. In [110], distributed MPC was provided as a method for minimizing heating utility expenses in multi-zone commercial buildings by using Benders' decomposition methodology. The proposed model was compared to the PI controller. Reference [111] demonstrated how to decentralize stochastic MPC with predetermined probabilities using the sub-gradient dual decomposition approach. The linear problem with an energy cost and a cost function for slack variables was solved using the linear programming approach. This research demonstrates that a distributed MPC results in a solution for a ten-zone construction is computed almost four times quicker computationally.

4.5. Data-Driven MPC

Inverse or data-driven MPC models are an alternative to physics-based MPC models [112, 113]. Data-driven models are very simple to create since they do not require knowledge of system physics. To train data-driven models, a comprehensive set of the system's input-output data under all possible operating conditions is required. As a result, the simplicity with which these models may be developed comes at the expense of diminished generalization capability when compared to physics-based MPC models. When training data differs from testing data, the accuracy of data-driven models drops significantly. As a result, it is necessary to train such models with data that covers all possible operating situations; this may be especially challenging for large-scale systems such as HVAC systems that run in a variety of weather circumstances during the year. Because models are trained under a limited set of circumstances and may not be sufficiently accurate under a different set of test settings, adaptive models are sometimes utilized. Alternatively, several researchers use distinct models for HVAC systems throughout the heating and cooling seasons.

Artificial neural network is the most widely used approach for modeling nonlinear systems owing to its excellent accuracy when compared to other methods. ANN simulates the human brain by using many neurons in various layers. Appropriately trained ANNs could accurately approximate any nonlinear process. There are several varieties of ANN architectures, but the most prevalent is the multi-layer perceptron structure [113]. ANN is integrated with an MPC model to propose a local and supervisory control framework for HVAC systems with air-cooled compressors [114], for a campus building with one AHU and one VAV [115], for an airport facility with five thermal zones [116, 117], for an HVAC system with VAV and AHU terminals in office buildings [118], for an autonomous air conditioning system with a compressor [119], for an office building with integrated natural ventilation [120], for a five-zone building [121], and for a school building [122].

4.6. Occupancy-based MPC

In buildings with variable occupancy level, advanced control systems rely heavily on information about occupant behavior. Information regarding occupancy states (e.g., presence/absence states) may be used to regulate setback temperatures to conserve energy during unoccupied times while maintaining sufficient thermal comfort for occupants upon arrival. Indeed, cooling an empty building's interior climate might result in unneeded HVAC operation and waste energy. Several features can be exploited to incorporate occupant behavior into predictive control systems. About 13 distinct characteristics have been distinguished in previous research to create occupancy prediction models. A judicious selection of those criteria may increase the prediction performance, given the range of available characteristics. Fig. 5 depicts the frequency of characteristics utilized to create occupancy prediction models. The time of day is the most often used feature, accounting for over 34%, followed by the day of the week, which accounted for about 16% of all features. It is evident that characteristics such as time of day, weekday, weekends, and seasons are the most likely to effect occupancy prediction performance, since there are apparent relationships between them with occupancy patterns. For instance, most people work during the day and sleep at night, or they organize their activities according on the day of the week. However, it remains unclear which qualities are the most beneficial and how many would provide the greatest outcomes.

Demand-controlled ventilation (DCV) is an energy-saving control approach that slows the pace of external air supply to a zone during times of partial occupancy. DCV modulates the ventilation rate over time depending on data from sensors that detect indoor air pollutants or occupancy. DCV has two possible benefits: improved management of indoor pollution concentrations and reduced energy use and peak energy demand. DCV has the greatest potential to be cost-effective in applications with the following characteristics: (I) a single or small number of pollutants dominate, such that ventilation sufficient to control the concentration of the dominant pollutants provides effective control of all other pollutants; (II) large buildings or rooms with unpredictable temporally variable occupancy or pollutant emission; and (III) climates with high heating or cooling loads. Currently, the majority of DCV systems are based on the monitoring and regulation of CO2 concentrations. Few well-documented case studies have quantified the energy savings and cost-effectiveness of DCV. The analyzed case studies demonstrate that in suitable applications, DCV may deliver considerable energy savings with a typical payback time of a few years.

Fig. 6 illustrates the frequency of utilizing various occupancy models. These models can be categorized into four classes: physics-based, data-driven, combination of physics-based and data-driven (hybrid), and time series models. Nearly 30% of all occupancy models are using Markov and proportional algorithms. These models are simple to develop and offer an acceptable degree of accuracy in the majority of instances. Following these models is data-driven models, which accounts for around 45% of all models. Data-driven

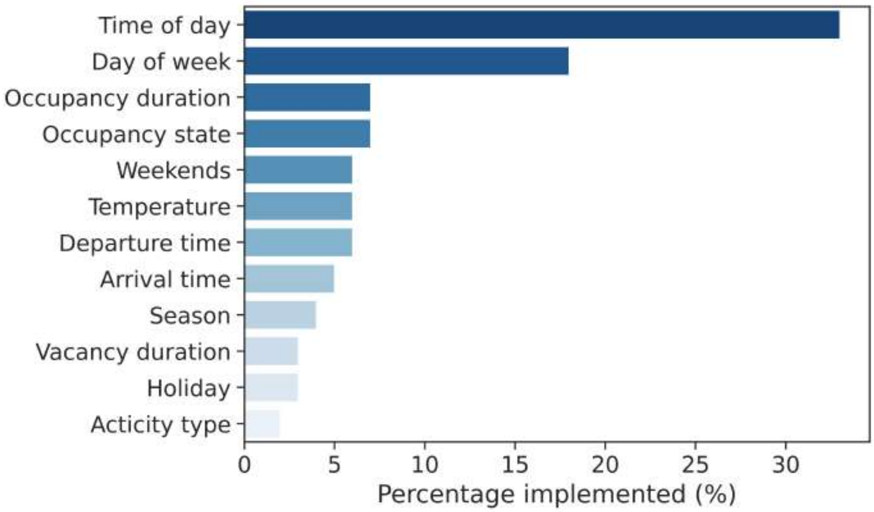

Figure 5: Frequency of various characteristics utilized for generating occupancy prediction models.

approach include constructing machine learning models, such as deep learning algorithms(LSTM, GRU, and RNN), Random Forest, Decision Trees, Logistic Regression, support vector machines (SVM), and K-means [123]. Other than these two dominating approaches, hybrid and time series forecasting models can also be found in the literature. The three primary forms of time series models are moving average, auto-regressive integrated moving average (ARIMA), and exponential smoothing. Occupancy-based MPC may be the subject of a separate research, since several occupancy level prediction models have been created in recent years for integration with sophisticated control techniques. Here, we attempted to present the topic as an emerging field of research and provide some data on the models produced; interested readers are referred to Ref [123] for an outstanding complete survey of the area.

To avoid dealing with complexities associated with occupancy prediction, some scholars developed simplified models. In [124], a mathematical approach for creating the energy characteristics of buildings and their heating systems, independent of the effect of their inhabitants, was introduced. Only the actual heat delivered to the heating system and the local exterior weather conditions (temperature, wind speed, and solar insolation) of a building are required as inputs. In terms of the corresponding external temperature, the result is a building energy model.

In [125], a practical tool for predicting the energy performance of a building based on a regression model for internal air temperature prediction and a variety of internal and external influencing elements is established. Consideration is given to the external climatic elements, such as outside air temperature, wind speed and direction, and solar heat gains dependent on the orientation of the building's fenestration surfaces. Internal variables consist of heating load, floor count, air exchange rate, etc. EnergyPlus may be combined with the proposed model to analyze the impact of time-varying variables on the thermal state of a building.

In [126], a data-driven approach is developed to combine the results of weather forecasting systems into energy consumption prediction models. This study is premised on the notion that an accurate forecast of future energy use will benefit all market participants and contribute to the creation of a cleaner and more sustainable energy system.

4.7. Computational Time

Due to recent advancements in methods for online solution of the underlying structured quadratic equations, linear MPC may now be implemented with remarkable speed. For linear systems with integer inputs, some (or all) of the MPC problem's decision variables are integer-valued, and the optimization problem underlying MPC is NP-hard (mixed) integer programming [127]. This category of systems may be represented as mixed logical dynamical systems [128], hybrid automata [129], or polyhedral piecewise affine systems [130].

In contrast to linear MPC, in which convex quadratic equations are often solved perfectly at each sampling time, nonlinear MPC necessitates the use of more complex algorithms, which need longer computing durations. Nonlinear MPC faces a conundrum: either the nonlinear iteration procedure is carried out until a pre-specified convergence criterion is met, which could result in significant feedback delays, or the procedure is terminated prematurely with only an approximate solution so that a pre-specified computation time limit can be met. Fortunately, significant progress has been made during the last decade, allowing both computational delays and approximation mistakes to be reduced.

Several strategies exist for online calculation of MPC using one or more approximation techniques to reduce complexity and computational time. For instance, the structure of the issue may be used to save computing effort, thresholds can be used to enable the controller to identify a suboptimal solution, and move blocking can be used to restrict the number of states. This method simplifies and restricts computations by grouping successive input signals. In spite of this, it is currently common to claim Nonlinear MPC computing rates are similar to those of MPC, if the appropriate algorithms are used.

4.8. Building Types

The percentage of various building types utilized as testbeds in the examined studies is shown in Fig. 7. It is evident that residential and office buildings accounted for majority of the prior study projects. This is because such structures make it easier for researchers to perform tests and gather the necessary data. In contrast, data collection in other kinds of commercial buildings may raise greater privacy concerns and has received less attention from academics. Commercial buildings such as halls, conference centers, and hotels make up 14% of the prior research, and there is less evidence about the efficacy of MPC HVAC management in industrial sector and other types of buildings. In order to get insight into the use of these control systems

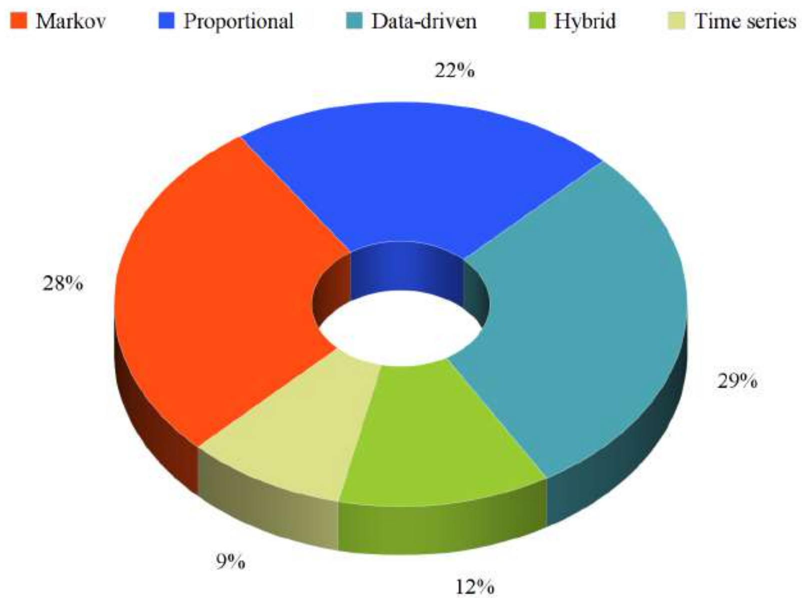

Figure 6: Breakdown of different models used for occupancy level prediction.

in a variety of case studies, it is advisable to investigate various testbeds as opposed to commercial and residential structures.

5. Opportunities and Challenges

When it comes to applying MPC to HVAC systems, there are both several obstacles and potential opportunities. We will discuss most of them in this section, including demand prediction, modeling, scaling formulations to handle huge systems, discrete optimization, and managing demand charges. These subjects will continue to be significant fields of academic investigation.

5.1. Demand prediction

Forecasts of future loads are required in order to make predictions using MPC modeling. Convection and radiation loads may be estimated using weather data and data-driven approaches. Also, historical data could be utilized to predict typical occupancy-related loads. This is usually accomplished using regression models or machine learning approaches, such as artificial neural networks [131]. Alternatively, stochastic approaches may be utilized to define uncertainty by generating the whole distribution of load profiles [132]. Generally, the farther into the future the prognosis, the higher the uncertainty in the projection.

As previously stated, prediction inaccuracies may be remedied by feedback. However, performance degradation may occur if considerable variations exist between predicted and real loads, since inefficient usage of thermal energy storage may occur. One significant problem in this area is determining how to update the complete future projection for MPC using current load readings. While there may be multiple viable options, it is unclear which one leads to the greatest control performance at the most minimal cost.

5.2. Modeling

Due to the predictive nature of MPC, a dynamic modelling of the system is required to connect commands to measured outputs. MPC decisions are often made on equipment operation and zone temperature setpoints, while measurable outputs are energy consumption and zone temperatures. As a result, MPC models comprise temperature dynamics for each zone, power consumption curves, and control laws for the regulatory

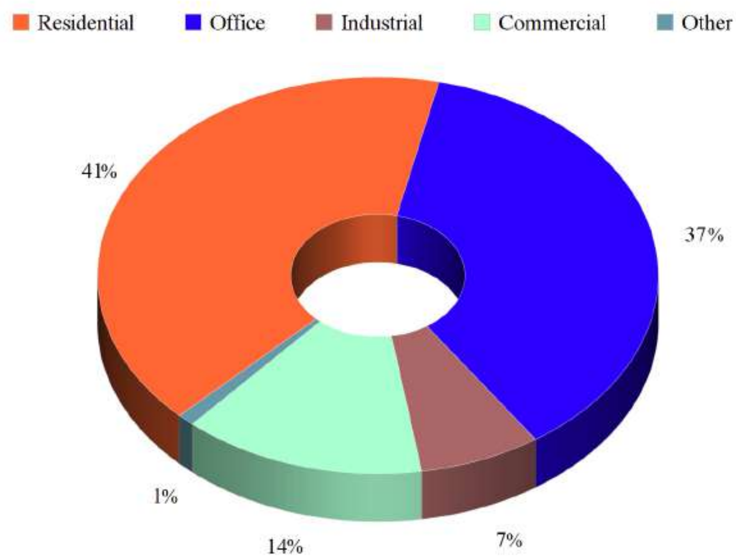

Figure 7: Breakdown of different buildings used to assess MPC systems in previous literature.

temperature controllers that receive the setpoints. Due to the extremely nonlinear character of buildings and the existence of massive disturbances, modeling MPC for HVAC may be difficult. Waterside equipment curves are seldom linear. Heat transfer coefficients are temperature dependent in energy balances; bilinear components originate from the product of temperatures and flow rates. Building regulatory control legislation are often logic or rule-based [133]. All of these nonlinearities may be challenging to adequately represent, which means that the resultant model may be unsuitable for real-time optimization. Multiple local solutions may exist for the ensuing nonlinear optimization issue. As a result, there is a trade-off between accuracy and simplicity in optimization.

Because modeling any building from the ground up may involve a significant amount of engineering time, operational data models may be used instead. Slow time-varying disturbances and weak sensors, also might make system identification difficult (i.e. Single thermostat readings may not accurately reflect the full zone mas). Structure may be introduced to the identification technique to minimize data needs, and grey-box models can be employed instead of black-box models [134]. In the last several decades, significant progress has been achieved in the creation of models that allow improved control over the energy consumption of system components while simultaneously guaranteeing a good interior environment in terms of thermal comfort and air quality. Nevertheless, selecting and implementing the most suitable modeling approach for enhancing the control strategy of HVAC systems is a continuous issue. In addition, it is obvious that almost every model contains a significant or small flaw resulting from underlying assumptions, unmeasured disturbances, or system property uncertainties. Due of the difficulty of modeling, the MPC design depends on feedback to adjust for model mistakes. Lower-order dynamical linear models may be employed for optimization as long as the mismatch is properly handled.

Based on the above discussion, there is no any “silver bullet” method to find the correct model match when it comes to the MPC control scheme for building and HVAC management. While the state-space model has been mostly utilized for modeling in prior investigations, different forms of black-box modeling are becoming more popular. White-box modeling approaches and simulation tools like Modelica, TRNSYS, and EnergyPlus are used to create complex building models that include detailed information on building behaviors and dynamics. Despite the fact that black-box models are becoming more popular for modeling, both physical and hybrid models are still viewed as having a distinct advantage over black-box models since less data is required to create either a physical or a hybrid model. When there is a degree of model mismatch, validation of the model is also necessary. Since few prior studies have explored model validation and the degree of mistakes connected with data-driven models, this is another gap that research needs to address.

5.3. Binary Parameters in Optimization

Discrete choices must be made during the optimization because the supervisory control system must determine when to switch equipment on and off in order to dispatch the equipment operating schedule. These discrete choices have traditionally been performed using heuristics or directly by human operators, resulting in significant cost reductions. When an active energy storage tank is incorporated, certain heuristic-based control solutions may actually result in higher running costs [135]. Modern computers, however, can handle such problems in acceptable time because of developments in hardware and methods for mixed-integer optimization. Because the application of mixed integer optimization for online control is still in its infancy, there may be implementation issues. Because MPC is new to the HVAC sector, there are less limits on what systems may be deployed than in other industries where MPC has been extensively utilized for decades and previous MPC systems would have to be replaced.

Such applications have sparked interest in learning more about the theory of MPC with binary actuators. Continuous decision variables are treated in traditional MPC theory. The stability theory, on the other hand, readily extends to handle the binary actuator scenario without extra limitations if proper assumptions about the constraint sets are made [136]. This new topic opens the door to a plethora of additional MPC applications using discrete actuators.

5.4. Large-Scale & Real-Time Applications

Typically, a single optimization model is defined and solved in most MPC applications. However, adopting a single monolithic MPC formulation for HVAC is complicated by the fact that many large-scale systems have hundreds of buildings and thousands of zones. Solving a single optimization problem in real time with both continuous and discrete choices is impractical for such applications, and such control systems are more complex to maintain. These concerns are alleviated by decomposing the concentrated problem into smaller sub-problems.

As described in [137, 138], distributed MPC can handle the optimization challenges of large-scale MPC. For different buildings, iterative approaches have been presented [139–141]. A disadvantage here is that these models may need several exchanges and iterations before reaching a solution due to the constraints imposed by current communication protocols in HVAC systems [142]. Using a decomposition technique to address the complete complexity of HVAC applications for these huge systems remains an outstanding research subject. Numerous plausible decompositions have been offered, but no consensus has been reached about which may become the gold standard.

5.5. Adaptive Demand Costs

Along with the time-varying energy costs, utility providers may impose a peak demand charge depending on peak power use during a certain period, for instance a month [143]. This peak demand fee is applied to all buildings and cannot be overlooked, since it accounts for a significant amount of the entire energy expenditure. MPC that is completely decentralized for each building cannot address the time-varying demand costs, since all buildings may pre-cool concurrently, resulting in a big peak. As a result, system-wide optimization is required to control when separate areas utilize energy. This characteristic highlights the need of a coordinating layer for managing the entire load. There is, however, no agreement on how to manage the demand charge in a genuinely distributed system without iteration.

5.6. Data-Driven MPC

model identification has typically been separated from controller design. An alternate approach is to see the identification process as a tuning parameter that should take the intended control application into consideration. In this regard, data-driven approaches for systemic analysis and control have grown in popularity. Traditional programming, rule-based models, if-then-else do this or that depending on what is known, will likely become obsolete in the next years due to the complexity of data and interactions between computers and humans. The significant evolution of coding maybe smaller in terms of size but is capable of performing complex procedures and controlling systems without the need of all of the well-known if-then-else conditions. Additionally, deep learning neural networks and reinforcement learning can be used to train the system to perform optimally over time.

Despite all of the benefits, only a few data-driven approaches provide theoretical assurances for system variable stability or constraint compliance. For instance, recent contributions [144, 145] provide an MPC method based on model-free data-driven MPC but provide no assurances of closed-loop stability and recursive feasibility, since appropriate lower constraints on the prediction horizon are not developed by data-driven MPC. Additionally, deriving satisfactory results from data-driven MPC remains an unresolved topic in the face of noise and uncertainty. Because no state measurement is utilized, data-driven MPC methods are essentially output-feedback MPC schemes. As a result of the measurement noise in the data, the suggested technique may be seen as a substitute for model-based robust MPC. Incorporating uncertainty explicitly into the formulation of the objective function and constraints has been a persistent concern in data-driven MPC. Additionally, it is commonly recognized that the uncertainties associated with a prediction algorithm have a role in determining the robustness of an MPC. A popular technique for simulating uncertainty is to introduce a constant noise component [146], which may be considered an oversimplification. On the other side, improper model selection might degrade the performance of MPC modelling.

5.6.1. Convexity and Computational Time of Data-Driven MPC

A data-driven decision is, at its core, a function that translates available training data to a possible action. This can be expressed as the minimizer of a data-driven surrogate optimization model. The out-of-sample risk, which is defined as the probability that the out-of-sample risk exceeds the optimal value of the surrogate optimization model of a data-driven decision, measures the quality of a data-driven optimization. Traditional models of decision-making under uncertainty require perfect knowledge, i.e. exact parameter values and probability distributions for random variables. However, such exact information is seldom accessible in reality, and a technique based on inaccurate inputs may be infeasible or perform poorly when executed. The optimal data-driven decision should therefore simultaneously minimize the out-of-sample risk with respect to all possible probability measures (and thus in particular with respect to the unknown true measure). Unfortunately, such ideal data-driven decisions are generally unavailable.

This motivates academics to seek data-driven decisions that minimize the out-of-sample risk subject to an upper bound on the out-of-sample disappointment, again simultaneously with respect to every conceivable probability measure. Consequently, in stochastic data-driven optimization, random variables are modeled as uncertain parameters belonging to a convex uncertainty set, and the decision-maker safeguards the system against the worst-case scenario within this set. Observations of random variables are used as direct inputs to mathematical programming problems in data-driven optimization. These assumptions helps reducing the computational time associated with the data-driven optimization algorithms.

Such Pareto-dominant data-driven decisions are shown to exist under conditions that permit interesting applications: the unknown data-generating probability measure must belong to a parametric ambiguity set, and the corresponding parameters must permit a sufficient statistic that satisfies the large deviation principle. If these conditions are satisfied, it is possible to demonstrate that the surrogate optimization model that generates the optimal data-driven decision must be a distributionally robust optimization problem constructed from the sufficient statistic and the rate function of its large deviation principle. This demonstrates that, in a strict statistical sense, the optimal method for mapping data to decisions is to solve a distributionally robust optimization model. This conclusion applies regardless of whether the original stochastic optimization problem is convex or not, and even if the training data are not independent and identically distributed.

6. Conclusion

Although HVAC system MPC control techniques have received considerable attention in recent years, however the most recent complete analysis was published in 2019. This critical review addresses this gap by examining technical papers, studies, and standards published over the previous two decades on the subject of MPC in HVAC's. This article will begin by providing a concise review of the technology. The authors discussed several HVAC control systems. Additionally, a bibliometrics study was undertaken to ascertain the significant research domains and trends throughout time. A thorough investigation of MPC implementation, application, optimization method, and modeling, as well as the overall picture of MPC control systems, has been conducted.

This comprehensive examination of the literature shed light on the limits of various approaches. These limitations are divided into such distinct categories as how features are used in the development of MPC models, what types of optimization models are available, what types of buildings are used as testbeds, what performance metrics are used to evaluate control systems and occupancy models, and what types of control systems are integrated with the systems. The bulk of MPC control systems have been investigated in terms of energy efficiency and thermal comfort; therefore, their success from other perspectives such as financial merits, demand-response management, and greenhouse gas emissions has not been adequately reviewed in the literature. In addition, despite the fact that there have been numerous studies on constructing MPC models, only a few research items have used more sophisticated algorithms, such as deep learning approaches, to capture more hidden patterns in relevant datasets. In addition, it was discovered that most of the prior research focused on MPC control systems in office or residential buildings. As a result, there is scant evidence in the literature on their effectiveness in other kinds of facilities, such as conference halls, schools, and manufacturing buildings. The following goals for future study effort are suggested based on the research gaps identified in this field:

- Evaluating the peak shifting, cost savings, and carbon dioxide emissions of various MPC-based HVAC controls.
- Identifying the attributes that have the strongest influence on MPC model performance.
- Using increasingly sophisticated approaches, such as deep learning, to uncover nonlinear patterns in load profiles, occupancy levels, renewable generation, and heat transfer dynamics in addition to using reinforcement learning to develop occupancy-based control algorithms and compare the results with MPC-based control.
- Developing and comparing the performance of occupancy-based HVAC control systems as a replacement for MPC.
- Conducting field assessments to determine the appropriate MPC-based control's effectiveness.
- Conducting experiments on testbeds other than residential buildings and office spaces.

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