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Review

Energy Modeling and Model Predictive Control for HVAC in Buildings: A Review of Current Research Trends

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Abstract: Buildings use up to 40% of the global primary energy and 30% of global greenhouse gas emissions, which may significantly impact climate change. Heating, ventilation, and air-conditioning (HVAC) systems are among the most significant contributors to global primary energy consumption and carbon gas emissions. Furthermore, HVAC energy demand is expected to rise in the future. Therefore, advancements in HVAC systems' performance and design would be critical for mitigating worldwide energy and environmental concerns. To make such advancements, energy modeling and model predictive control (MPC) play an imperative role in designing and operating HVAC systems effectively. Building energy simulations and analysis techniques effectively implement HVAC control schemes in the building system design and operation phases, and thus provide quantitative insights into the behaviors of the HVAC energy flow for architects and engineers. Extensive research and advanced HVAC modeling/control techniques have emerged to provide better solutions in response to the issues. This study reviews building energy modeling techniques and state-of-the-art updates of MPC in HVAC applications based on the most recent research articles (e.g., from MDPI's and Elsevier's databases). For the review process, the investigation of relevant keywords and context-based collected data is first carried out to overview their frequency and distribution comprehensively. Then, this review study narrows the topic selection and search scopes to focus on relevant research papers and extract relevant information and outcomes. Finally, a systematic review approach is adopted based on the collected review and research papers to overview the advancements in building system modeling and MPC technologies. This study reveals that advanced building energy modeling is crucial in implementing the MPC-based control and operation design to reduce building energy consumption and cost. This paper presents the details of major modeling techniques, including white-box, grey-box, and black-box modeling approaches. This paper also provides future insights into the advanced HVAC control and operation design for researchers in relevant research and practical fields.

Keywords: advanced HVAC technology; building energy modeling; white-box model; grey-box model; black-box model; building HVAC optimization; HVAC model predictive control (MPC)

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1. Introduction

The building sectors (e.g., commercial and residential buildings) account for about 40% of total global primary energy use and about 30% of global greenhouse gas (GHG) emissions [1]. According to the U.S. Energy Information Administration (EIA) [2], the share of the global delivered energy consumption in buildings could be expected to keep increasing from 20% in 2018 to 22% in 2050. Among the energy-related factors in a building, cooling, heating, and the relevant subsystems are the major components of the building energy consumption. In this way, improving a building's heating, ventilation, and air-conditioning (HVAC) and its associated systems has played a crucial role in energy and emission reductions [3]. Because of the complexity of building energy systems' design and operation, various aspects, such as the system's transient energy flow and indoor/outdoor heat interactions, need to be reflected in its design and operation process to increase the overall energy efficiency of HVAC systems [4]. HVAC systems, which provide the cooling and heating supply into a building's thermal zones, can consist of diverse subsystem configurations, including air-loop systems (e.g., heating/cooling coils and supply/return air fans) and water-loop systems (e.g., chillers, boilers, heat exchangers, cooling towers, and water pumps). In addition, the HVAC systems of modern buildings need to satisfactorily deal with various interrelated variables (e.g., temperature, humidity, and velocity) against changeable external disturbances (i.e., outdoor weather conditions) to provide appropriate thermal comfort to occupants [5,6].

In response to this complexity, whole building or system level energy simulations have been widely used to assess appropriate options for energy demand reduction while meeting the indoor thermal comfort requirements and resolving the environmental issues. A good overview of the detailed fundamentals, features of energy-related systems, and main applications for building energy systems and their calculations is given by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [7,8]. According to the report [8], HVAC systems need to be operated with appropriate control schemes because they are major contributors to the whole building's energy and thermal comfort, keeping the desired environment for occupants inside buildings. There are many considerations during a building energy and heat system analysis, including building age, locations, building envelope materials, energy-related systems, and size. As computational intelligence for building energy system applications is becoming an essential part of the building design and energy management processes [9], the importance of comprehensive energy simulation modeling has been re-emphasized and highlighted. A simulation analysis of heating and cooling systems has become essential at the early design stage and the remedial option stage in the case of new and existing buildings, respectively [10].

The current energy-related modeling techniques, involving the prediction, management, and optimization of the building energy systems design and control, can be grouped into three categories [11], physics-based modeling (i.e., white-box models), data-driven modeling (i.e., black-box models), and hybrid modeling (i.e., grey-box models), by reflecting both physical laws and data-based models. Building energy-related analysis tools and approaches is based on the three methods required to predict thermal and/or energy behaviors and analyze interactions between many connected parts for the building thermal zones and integrated cooling and heating systems. Those modeling approaches can be used to investigate indoor thermal requirements and occupant's needs, which generally depend on the individual performance of energy-relevant sublevel parts (e.g., internal heat gains, HVAC-related systems, and other connected systems). The whole-building energy performance is also integrated by considering the individual components in a building [12]. Since the whole-building energy performance within a building is based on many subsystem components, building energy-related analysis tools can be separated by different options, including building design tools, independent modeling tools of building energy-relevant subsystems, and detailed whole-building energy simulation programs. In addition, many whole-building energy simulation tools and applicable prediction methods exist to determine energy analysis indicators for different design scenarios to minimize energy costs and peak energy consumption [12,13]. For this review, this study focuses on heating and cooling energy-related systems (e.g., HVAC systems), including modeling approaches and integrated control techniques.

To operate HVAC systems more efficiently, the appropriate control and operation of the energy-related systems are key techniques. Since HVAC-related systems of modern buildings consist of many different types of subsystem configurations with a dynamic operation [14], controlling HVAC systems in an effective way between multiple goals (e.g., energy reduction and occupant comfort) is still challenging, specifically in finding the optimal control signals and operating multiple systems simultaneously within a building. The rule-based reactive control strategy is commonly used for traditional HVAC control systems, including pre-determined or tracked schedules [15]. The pre-determined schedules can be used to select proper temperature setpoints based on heuristic rules. The tracked setpoint input schedules can be determined based on the difference between variables (e.g., temperature, pressure, and flow) using techniques such as the proportional, integral, and derivate (PID) control [16]. The rule-based control strategies can also be facilitated to reduce the building energy usage, and thus, GHG emissions, by adjusting the setpoint signals based on an interactive heuristic approach. Although the rule-based feedback control algorithm has been widely adopted for building controls because it is relatively simple and effective for building applications, it is still challenging to have optimal solutions, typically when it must be customized to dynamic response events or seasonal weather conditions [15]. One effective method to resolve such control issues for energy- and environmental-efficient buildings is the model predictive control (MPC) approach [17]. The application of the MPC method for buildings has been actively studied and implemented due to its capability of solving an optimization problem at every decision moment by satisfying conflicting goals, such as energy reduction and indoor thermal comfort. Lately, its application is becoming more powerful because most modern buildings are equipped and connected with complicated heat systems and/or on-site intermittent systems, such as renewables and/or grid connections. In addition, the recent trends in the affordable cost of relevant hardware components (e.g., controllers, communication infrastructure, and sensors) and the ease of application have led to the success of the MPC for building applications [18,19].

Given that MPC applications can effectively predict a building's future behaviors (e.g., thermal demands and/or energy savings), using building modeling tools and/or developed mathematical models are essentially considered. As mentioned earlier, three energy modeling categories can be used for building applications with the MPC framework [20]. According to the problem formulation, the three modeling approaches have different challenges and applicability to the MPC. Many recent studies on MPC have been conducted for intelligent building operations by focusing on energy reduction and/or minimization with simultaneous indoor thermal comfort improvement. For instance, Drgona et al. [21] provide a good overview of advanced building control methods by addressing a unified framework of building MPC technologies for real-world applications. Based on their conclusion, although there still have been challenges in MPC market penetration based on the advanced stage of relevant research fields, large-scale MPC implementation in a marketplace could be expected to take place over the coming years because MPC is the most promising solution and has been actively studied for reductions in building HVAC energy and environmental issues. Despite a large number of existing studies on building energy modeling and its advanced operation fields, a comprehensive review of many recent advancements is still needed because practical applications and adoptions by built-environment engineers are in their early stages. In addition, the technology development in such fields has rapidly evolved in response to the fast transition to energy management technologies and practical applications for buildings and building-connected systems.

Based on the above observations and further considerations, this review study aims to deliver a thorough review of building energy modeling techniques and state-of-the-art updates for MPC HVAC applications associated with the modeling techniques by reviewing the most recent research articles in this field based on a database search. More specifically, the key contributions of this review study are summarized as follows:

- This study introduces the advancements of currently applicable energy modeling tools and methods that can be applied to assess building energy performance and can be integrated with HVAC control and optimization.
- This study investigates recent research articles based on the three applicable building energy modeling approaches (i.e., white-box, grey-box, and black-box modeling approaches) and their research-based applications.

- This study also provides an overview of MPC-based HVAC operation methods and their practical applications based on published research papers. This part reviews the major subsystem configurations (e.g., the air-loop and water-loop demand/supply sides) of HVAC-related systems with dynamic operation and control methods.
- This study, finally, highlights the conflicting issues and future insights into the optimized control and operation of HVAC based on energy modeling-based approaches for smart and integrated buildings.

The rest of the paper is organized as follows. Section 2 provides a systematic review process based on a database search. The review of three major energy modeling approaches (i.e., white-box, grey-box, and black-box modeling approaches) is presented in Section 3. This section introduces modeling details of the three approaches, and each modeling method's relevant research papers are summarized. Section 4 comprehensively reviews the MPC-based energy modeling, controlling, and optimization studies by focusing on radiant cooling and heating, the air-handling unit, the electric heat pump-based HVAC, and chiller systems. Section 5 gives both the conclusions and discussion based on recent advancements, challenges, and directions for future works.

2. Systematic Review Process

This review study first investigated relevant keywords and context-based collected data to comprehensively overview their frequency and distribution. Then, to narrow the study selection and search scopes, this study focused on and analyzed relevant review-type articles published primarily since 2000 by classifying keywords and application types. Then, research-type papers were reviewed to extract informative and useful outcomes for a systematic review by highlighting the most recent findings in energy simulation methods, tools, and applications in building energy system fields.

Figure 1 presents the overall workflow of the systematic review process based on the available published articles regarding energy modeling techniques, MPC-based HVAC control, and optimized operation schemes in buildings. The current whole-building energy modeling and prediction, management, and optimization techniques for energy performance of integrated buildings can be grouped into three categories: physics-based modeling (i.e., white-box models), hybrid modeling (i.e., grey-box models), and data-driven modeling (i.e., black-box models). Based on those categories, search scopes and research types were narrowed for more detailed investigations on such items. The overall topics focus on whole-building energy simulation tools, energy system modeling for building connected applications, data-driven building energy prediction, model predictive control and optimization, and white-box, black-box, and grey-box models regarding energy and environmental systems for building applications. In addition, published journal articles since 2010 based on MDPI's and Elsevier's databases (e.g., found through Google Scholar, MDPI's open access journal list [22], Scopus, and ScienceDirect [23]) were collected to overview each paper's major objectives, methodologies, limitations, and future challenges. It should be noted that for all the papers used for this review study, about 80% of them are based on Elsevier's database.

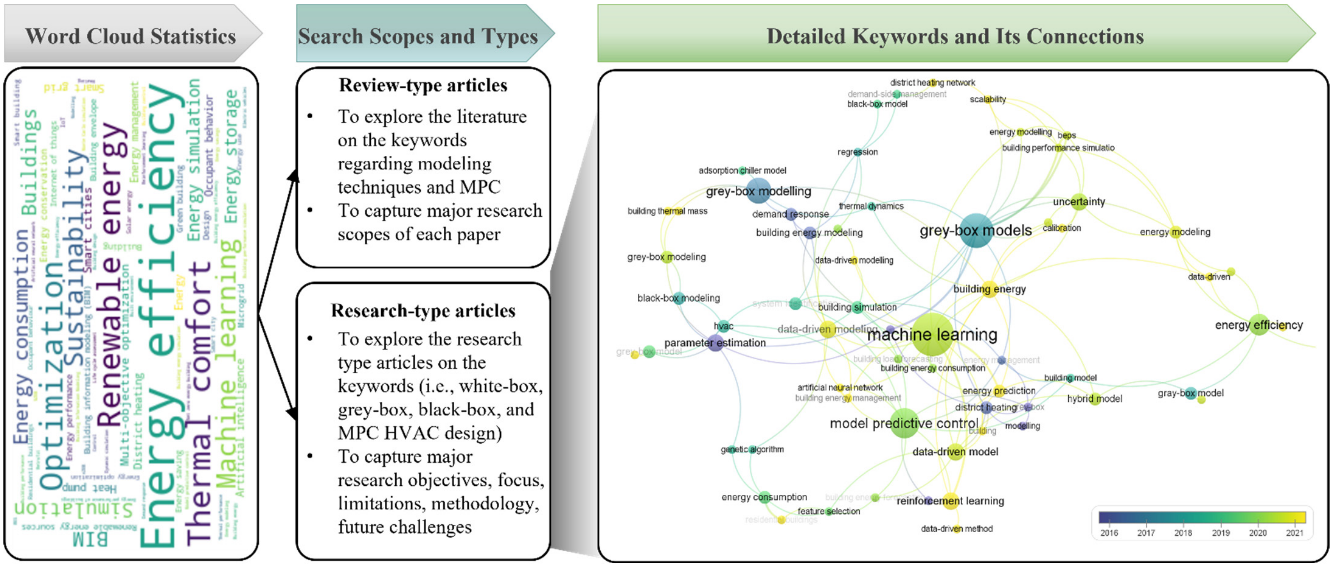

Figure 1. Review process workflow for HVAC energy modeling, control, and optimization in smart building applications.

3. Building Energy Modeling Approaches

3.1. White-Box Modeling Approaches

The white-box modeling methods (known as the physical-based or engineering methods) use physical principles to solve the calculation of thermal and energy behaviors on the whole-building level or for sublevel systems in buildings [24]. A series of mathematical models are built up step-by-step based on elaborate physical functions or thermodynamics of the mass and energy balances, momentum, and flow balance [25]. The common way of making a white-box model for building energy modeling is as follows: building geometry/envelope, internal heat gains (e.g., lights and occupants), sublevel systems (e.g., HVAC and renewable systems), and control and management parameters. Because of such required parameters that involve the building itself and its environmental information, the modeling is relatively complex and time-consuming to obtain adequate and accurate results corresponding to realistic situations in buildings [26].

Although a wide collection of building energy modeling tools was used throughout the building energy community, most tools were traditionally created for design applications, detailed system simulations, and simple operation managements based on homeostatic short-term feedback mechanisms [27,28]. In the case of white-box modeling approaches, building energy modeling tools typically serve the thermal and HVAC system performance analysis of buildings individually based on the definitive input data of building geometries, HVAC systems, internal heat gains, and weather data [12]. The U.S. Department of Energy (DOE) provides a directory of building-related energy modeling tools, as shown in Figure 2, which have been traditionally and recently used to improve HVAC energy efficiency or incorporate renewable energy systems to enable the smart building performance [29].

Hong et al. [12] reviewed the state-of-the-art methodologies on the development and application of computer-aided building modeling tools. In their survey of various building energy modeling tools, only a few simulation tools were available in the public domain even though numerous building design and HVAC system simulation tools were used throughout the building communities. In addition, they mentioned building energy modeling tools that were registered in the International Energy Agency (IEA) Energy Conservation in Buildings and Community Systems (ECBCS) Programme, such as DOE-2, COMIS, and TRNSYS. Their study proved it to be challenging to compare building energy simulation programs in absolute ways because each building simulation tool had its advantages and disadvantages regarding building thermal load and HVAC system levels. Figure 2a illustrates the building energy simulation tools available for the building thermal load analysis and HVAC system supports. Additionally, Figure 2b shows the public and private sector simulation tools and co-simulation services through the OpenStudio Platform. Based on this platform, a co-simulation analysis can be performed for a more advanced assessment, including to assess system size and real-time optimization, detailed visual comfort analysis, novel HVAC system implementation, etc. [30].

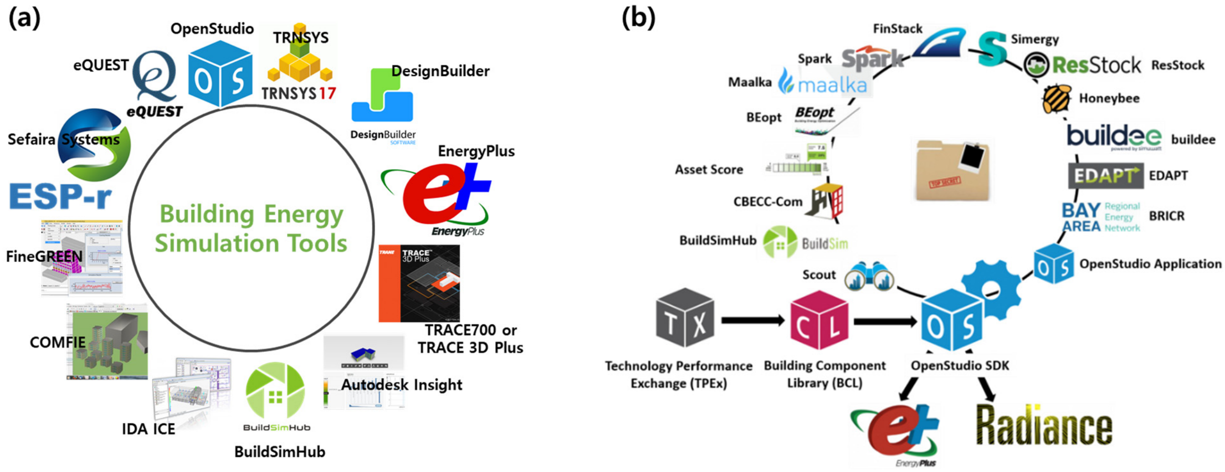

Figure 2. (**a**) Building energy modeling tools found in BEST Directory [31] and (**b**) public and private sector tools and services via the OpenStudio Platform that EnergyPlus directly supports [32].

In reference [13], the features of twenty widely used building energy simulation tools were reviewed, including BLAST, BSim, DeST, DOE-2.1, eQUEST, EnergyPlus, ECOTECT, Esp-r, IES, TRNSYS, etc. Crawley et al. [13] also provided detailed trends about building energy modeling tools and compared the features of building simulation tools based on different categories (e.g., general modeling features, zone thermal loads, infiltration, and HVAC systems). Ercan [33] also provided a systematic review of current software tools (e.g., EnergyPlus, TRNSYS, Modelica/Dymola and MATLAB/Simulink) by focusing on the advanced model-based energy evaluation and operation control for building applications associated with HVAC and renewable energy systems.

Those studies [12,13,33] mostly reviewed an extensive list of building energy modeling tools and provided summaries of the current building energy modeling tools, including advantages and disadvantages. This part of the review paper will focus on the existing literature, adopting energy modeling tools and techniques to analyze and implement energy-efficient HVAC-related technologies for building applications. Table 1 lists the representative reviewed research articles regarding white-box models.

Table 1. List of the representative reviewed papers regarding "white-box" models for building energy simulation.

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
Coffey et al. [27]	2010	Development of a flexible modeling framework using GenOpt for MPC.	Co-simulation approach with EnergyPlus and TRNSYS.
Beausoleil-Morrison et al. [34]	2012	Development of an integrated system using energy conversion, storage, and distribution technologies for existing whole-building energy simulation tools.	Co-simulation between TRNSYS and ESP-r.
A. L. Pisello et al. [35]	2012	Methodologies to reduce building energy demands through post-occupancy assessment and to optimize building operations.	Modeling and performance evaluation for optimization strategy using EnergyPlus.
Li and Wen [36]	2014	Development of building energy estimation model for online building control and optimization based on a system identification approach.	Online modeling using EnergyPlus and MATLAB.

Table 1. *Cont.*

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
Dirks et al. [37]	2015	Impact study of climate change on peak and annual building energy use.	Multi-simulation using EnergyPlus.
Davila et al. [38]	2016	Development and validation of an urban building energy model to assess citywide hourly energy demands at building levels.	Modeling and performance evaluation using EnergyPlus.
Oak [39]	2016	Development of the control system using building energy control patterns in response to weather changes.	Co-simulation between BIM and CFD.
Pang et al. [40]	2016	Development of the real-time simulation framework using FMI (functional mockup interface) and FMU (functional mockup units).	Co-simulation with EnergyPlus.
Seo and Lee [41]	2016	Analyzed part load ration (PLR) and operation features with VAV system to evaluate energy savings potential.	Modeling and performance evaluation using EnergyPlus.
Ng and Payne [42]	2016	Evaluated energy savings potential of ventilation-related energy systems such as HRV and ERV.	Modeling and performance evaluation using TRNSYS.
Chen et al. [43]	2017	Presented the retrofit analysis feature to automatically create and simulate urban building energy models.	Open web-based modeling platform with EnergyPlus.
Kim et al. [44]	2017	Performance evaluation of VRF and RTU-VAV systems under US climate conditions.	Modeling and performance evaluation using EnergyPlus.
Yun and Song [45]	2017	Development of automatic calibration method to reduce the errors between simulated and measured HVAC energy use.	Automated calibration using EnergyPlus.
Alimohammadisagvand et al. [46]	2018	Investigated the effect of demand response (DR) on building energy use and cost.	Modeling and performance evaluation using IDA ICE.
An et al. [47]	2018	Assessed cooling and heating performance of an office building with building-integrated PV windows.	Modeling and performance evaluation using EnergyPlus.
Fernandez et al. [48]	2018	Evaluated energy savings potential of energy-efficient measures in commercial buildings under US climate zones.	Multi-simulation using EnergyPlus.
Wu and Skye [49]	2018	Evaluated energy and cost savings potential of HVAC and renewable systems under US climate conditions.	Modeling and performance evaluation using TRNSYS.
Kim et al. [50]	2018	Investigated the daylighting and thermal effects of a double skin façade system with interior and exterior blind controls.	Modeling and performance evaluation using EnergyPlus and Dysim.
Kim et al. [51]	2018	Presented the detailed procedures for model calibration of a VRF system with a dedicated outdoor air system.	Modeling and calibration using EnergyPlus.
Wu et al. [52]	2018	Investigated commercially available HVAC technologies in terms of energy, comfort, and economic performance for a residential building.	Modeling and performance evaluation using TRNSYS.
Yu et al. [53]	2018	Conducted the comparative analysis to evaluate HVAC energy savings potential of the UFAD system.	Modeling and performance evaluation using EnergyPlus.
Kim et al. [54]	2019	Presented a methodology of validating fault models that can be used with the building energy simulation tool.	Modeling and calibration using EnergyPlus.
Lee et al. [55]	2019	Investigated the part load ratio and the operating characteristics of a gas boiler to enable energy savings.	Modeling and performance evaluation using EnergyPlus.
Min et al. [56]	2019	Evaluated the energy performance of a multi-split VRF system based on bypass and injection cycles using a numerical simulation.	Modeling and performance evaluation using physics-based mathematical models.
Taddet et al. [57]	2019	Real-time building simulation by implementing a data communication chain in EnergyPlus with hardware-in-loop integration for optimal HVAC operation.	Co-simulation with EnergyPlus.
Guyot et al. [58]	2020	Manual calibration of dynamic heating and cooling systems was conducted using a real office building with 132 zones.	Modeling and calibration using EnergyPlus.
N. Kampelis et al. [59]	2020	Development of a building energy simulation model and calibration based on a trial-and-error approach.	Modeling using EnergyPlus and calibration based on a trial-and-error approach and Kalman filtering.
Cucca and Ianakiev [60]	2020	Development of the co-simulation tool coupling the model of a building energy system with Dymola/Modelica and EnergyPlus.	Co-simulation with EnergyPlus.
Im et al. [61]	2020	Investigated key influential parameters in estimating the uncertainty of energy savings and performed uncertainty quantification for several different scenarios.	Modeling and performance evaluation using EnergyPlus.
Y. Kwak et al. [62]	2020	Proposed a flexible modeling approach to develop a reference building for energy analysis based on parametric analysis.	Modeling and parametric analysis using EnergyPlus.
Seo et al. [63]	2020	Assessment of the cooling energy performance between chiller-based conventional AHU systems and water-cooled VRF-HP.	Co-simulation with EnergyPlus.
A. Rosato et al. [64]	2020	Development and validation of a dynamic building simulation model for fault detection and diagnostics (FDD).	Modeling and fault detection/diagnostics (FDD) using TRNSYS.

Table 1. *Cont.*

Source	Year	The Focus of Article (Objectives)	Software and Features (White Box-Based Tool)
Calixto-Aguirre et al. [65]	2021	Proposed a methodology for the validation of non-airconditioned building thermal simulation to increase building energy efficiency.	Modeling and performance evaluation using EnergyPlus.
Ascione et al. [66]	2021	Development of user-friendly tool for building energy modeling and simulation.	Co-simulation using EnergyPlus and MATLAB.
Bampoulas et al. [67]	2021	Presented an energy quantification framework for various residential building energy systems.	Modeling and performance evaluation using EnergyPlus.
Martinez-Marino et al. [68]	2021	Simulated indoor thermal conditions in a multi-zone building using a co-simulation method.	Co-simulation using TRNSYS and MATLAB.
Piccinini et al. [69]	2021	Development of a novel reduced-order model technology framework for energy savings through cost-effective energy measures.	Modeling and calibration using Modelica ROM.
R. D-Tumeniene et al. [70]	2021	Development of a building energy model for an administrative building and model calibration with measured data.	Modeling and calibration based on an EnergyPlus engine simulation tool.
Neves et al. [71]	2021	Investigated the energy and cost impact of geothermal heat pump systems.	Modeling and performance evaluation using EnergyPlus.

Based on the reviewed papers, the challenge of the current studies is to better integrate the whole simulation into design applications and detailed system processes for improving the quality management [72]. Building energy modeling tools for future smart buildings require automated operation by integrating with a real-time control algorithm in the decision-making process under various built-environments [40]. Co-simulation can overcome the disadvantages of each simulation tool by linking two or more simulation tools together by exchanging run-time data [73]. The development of co-simulation can also provide more accurate predictions, including about the HVAC system, plant sizing, and occupant thermal comfort [74].

EnergyPlus is a widely used new-generated program developed by the U.S. Department Of Energy (DOE) [75]. With the co-simulation process, the building system manager manipulates the data interaction and data exchange between EnergyPlus and other linked tools, such as SPARK and TRANSYS modeling tools [76]. For enabling optimized building control, co-simulation between EnergyPlus and Simulink through a building control virtual testbed (BCVTB) and MLE+ is the current best practice [77,78]. A functional mock-up interface (FMI) and functional mock-up unit (FMU) for co-simulation, developed by the Lawrence Berkeley National Laboratory (LBNL), are also good middleware for the improvement of computing techniques. The FMI and FMU can couple several different simulation tools (e.g., EnergyPlus, TRNSYS, MATLAB/Simulink, Python, and LabView). The middleware can allow data interaction and exchange between simulation programs and real building automation systems (BASs) that can be developed for existing or novel HVAC systems and their practical applications [41,61]. Modelica is the open standard of an equation-based, object-oriented, and non-proprietary modeling language that has been used in various building applications [79,80]. Since dynamic building energy models for thermal and HVAC component analysis are developed in Modelica, it can be a proper tool for control purposes in future smart buildings [34,79]. TRNSYS is an extensible simulation tool for the whole-building energy simulation, including single- and/or multi-zone buildings [81]. The TRNSYS simulation solves algebraic and differential equations of physics-based energy systems in a whole building. TRNSYS's building energy simulation can provide engineers and researchers with diverse system analyses, from simple systems to advanced HVAC system designs, including HVAC control strategies, renewable energy systems (wind, solar, photovoltaic, hydrogen systems), etc. For pre- and/or post-processing co-simulation, TRNSYS is also able to link with other software tools using a middleware framework (e.g., Microsoft Excel, MATLAB/Simulink, COMIS, etc.) [82]. Esp-r, developed in 1977 by the Energy Systems Research Unit at the University of Strathclyde, is the European reference building simulation program. Esp-r is capable of modeling thermal zones and simulating the energy flows within combined building HVAC systems with user-specified control actions [83]. In addition, co-simulation between Esp-r and TRNSYS simulation tools or other co-simulation frameworks (e.g., MATLAB/Simulink) allows the strengths of both simulation tools to enable the modeling of innovative buildings and energy system designs [35].

3.2. Grey-Box Modeling Approaches

Grey-box modeling approaches, known as "semi-physical" or "hybrid" modeling methods, combines white- and black-box modeling approaches by considering a hybrid structure with first-principle physics and data-driven strategies [84]. This approach includes the first-principle equations to develop simplified physical processes occurring in the system, and the equations developed from statistical methods and experimental data to improve modeling efficiency with less-understood relationships [85]. The grey-box algorithms include the advantages and shortcomings of the other two methods to represent the system's actual behavior and efficiently deliver those methods' benefits [86]. Figure 3 illustrates a typical process and the data requirements for developing a grey-box model. This method can be more computationally efficient than the white-box method and offers flexibility and scalable applications in a model design phase to facilitate the evaluation of energy-efficient means at single or multiple building system levels [87]. This method has been widely used for evaluating energy optimization scenarios when considering building HVAC control or smart-connected system applications [26].

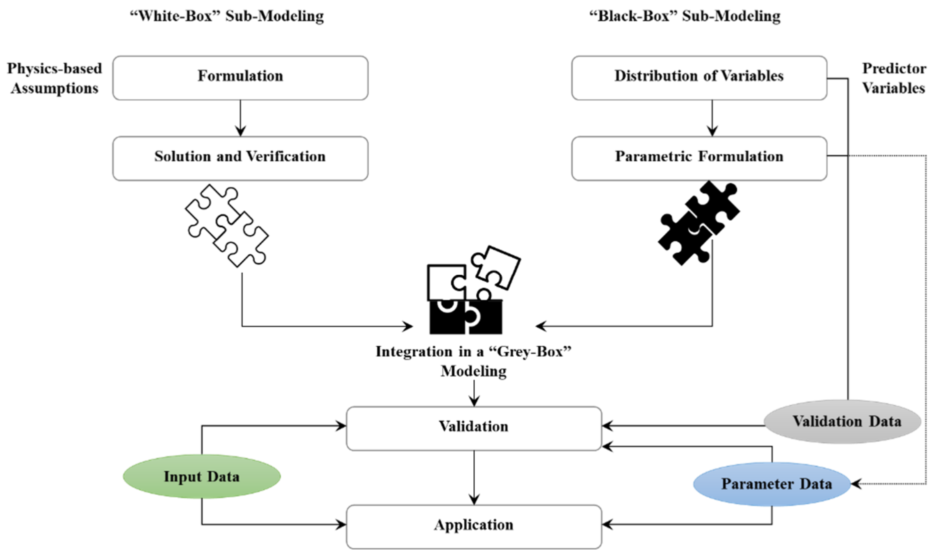

Figure 3. Schematic of the development process of a "grey-box" model, reprinted with permission from Ref. [84].

A resistance-capacitance (RC) or thermal network model is commonly used to create grey-box models. Although there are several challenges, such as theoretical limitations and confusing model structures, this approach has been used for many research topics in building energy-related and/or HVAC systems because of the benefits, including: (1) a faster calculation with simplified physics-based models and (2) online controls [26]. The thermal conditions of a building can be expressed with an electric circuit analogy with multiple parameters (i.e., the number of thermal resistances and capacitances) of the model obtained from the measured data, considering available physical insights [88].

The grey-box models can be created based on two subcategories: (1) the physical approach and (2) the semi-physical approach [89]. The major difference between the physical and semi-physical approaches is model structures. For the physical approach, the model structure can be built based on physical models, and the parameters used for the physical models are typically estimated from the measured data. Zhang et al. [90] provided an excellent example of the physical approach for grey-box modeling. Zhang's study proposed a dynamic, simplified RC-network model for a building ventilation system and obtained the parameter identification effectiveness using experimental data. The semi-physical approaches use physical insights to guide the data through data-driven models. Hossain et al. [91] presented a grey-box modeling approach that uses the Bayesian neural network method to estimate the parameters of a grey-box thermal model with a training dataset. Numerous hybrid model structures of grey-box modeling have been used in the literature. The common grey-box model comprises one first-principle physical submodel and one black-box based submodel with parallel and serial arrangements, even though the number and type of submodels can vary according to application features [92].

The energy modeling of buildings' HVAC and their subsystems or community levels has multiple roles, such as thermal behavior estimation, HVAC size design and optimization, and subsystem/urban energy controls, including real-time operation [93]. For the grey-box modeling approaches, there are numerous representations of research articles regarding RC modeling for building envelopes, single- or multi-zone modeling with internal/exchanged heat gains (e.g., zone air mixed, electrical heat gains, and infiltration), and simplified building HVAC models or district/urban energy prediction models. Among the existing research articles, the topics of thermal load calculation, HVAC operation control/operation, and optimization based on MPC frameworks are relatively dominant for buildings' HVAC and their connected applications [26]. Table 2 summarizes the list of the more representative papers reviewed for this paper, focusing on the grey-box models for the building thermal load and HVAC energy simulation. Because parameter identification is a significant process for grey-box model development, this table also presents how they obtained and/or assumed the parameter identification data for each study. Those parameter values are generally identified based on measured data and/or simulation assumptions.

Table 2. List of the representative reviewed papers regarding "grey-box" models for building thermal load and HVAC energy simulation.

Source	Year	The Focus of Article (Objectives)	Parameter Identification (or Other Features)
Nielsen and Madsen [94]	2006	Evaluated the heat consumption of a large district heating system using a grey-box modeling approach.	Experimental identification with measured heat consumption and climate data.
Kampf and Robinson [95]	2007	Development of a grey-box model to simulate heat flows for a building with an arbitrary number of zones.	Assumed identification and ESP-r were used for model verification.
Balan et al. [96]	2011	To simulate the thermal behavior of a building for energy reduction using a simplified thermal-network grey-box model.	Experimental identification of the model's parameters.
Berthou et al. [97]	2014	Development and validation of a grey-box model by adopting a second-order model to predict thermal behavior in an office building.	Experimental data for the identification process and sensitivity analysis to identify the most important parameters.
Reynders et al. [98]	2014	Development of a robust grey-box model that results in an accurate prediction and long-term simulation in a residential building.	Experimental identification for reliable characterization of the physical properties.
Unerwood [99]	2014	Development of an improved method for the simplified modeling of the thermal response of building components using a 5-parameter second-order grey-box model.	The extraction of the simplified model parameters based on a multi-objective function algorithm.
Ogunsola and Song [100]	2015	A simplified RC thermal model using an analytical solution method for an office building.	Experimental data for the identification process and the developed RC model was compared with measured data and a white-box model.
Teres-Zubiaga et al. [101]	2015	Evaluated the thermal performance of a residential building with a grey-box model.	Experimental data for the identification process and improving accuracy.
Jara et al. [102]	2016	Presented the self-adjusting RC-network model for the parameter identification of a simplified lumped parameter model.	First-order method with two resistances, one capacitance, and simulated data used for the identification process.
Ji et al. [103]	2016	Development of the RC-network model with a submetering system for cooling load calculation in a commercial building.	For the identification process, measured data from real buildings and simulated data from an EnergyPlus model were used.
Zhang et al. [90]	2016	Proposed a dynamic, simplified RC-network model for radiant ceiling cooling system integrated with an underfloor ventilation system.	The parameter identification effectiveness determined by experimental data.
Hu and Wang [104]	2017	Development of a self-learning grey-box thermal model to investigate demand response for a HVAC system.	Pre-estimated and scaled parameters for the identification process using measured data.

Table 2. *Cont.*

Source	Year	The Focus of Article (Objectives)	Parameter Identification (or Other Features)
Li et al. [105]	2017	Simplified RC-network model development and validation for the pipe-embedded concrete radiant floor system.	RC model with two resistances and one capacitance (2R1C), and validation through numerical simulation and experimental data.
Afram et al. [106]	2018	Development of a grey-box model for a residential HVAC system with heat recovery ventilator and air-source heat pump.	Experimental data for the identification process and the developed model was compared with measured data for validation.
Gori and Elwell [107]	2018	Development of a method for the quantification of systematic errors on the thermophysical properties of buildings using a dynamic grey-box model.	Experimental data for the identification process and the comparison against the static method.
Macarulla et al. [108]	2018	Assessment of the potential of using the stochastic grey-box modeling approach to estimate the ventilation air change rate.	Tracer-gas mass balance and experimental data used for the identification process.
P. Bahramnia et al. [109]	2019	Development of a RC-network model and implementation of a model predictive control strategy to optimize both temperature and humidity operations.	Experimental data for the identification process and the developed model was compared with measured data by minimizing the optimization index.
Shamsi et al. [110]	2020	An uncertainty framework for reduced-order grey-box energy models in heat demand predictions of the building stock.	The identification process of using an integrated uncertainty approach using a copula-based theory and nested fuzzy Monte Carlo approach.
Thilker et al. [111]	2021	Development of a nonlinear grey-box model for the heat dynamics of a school building with a water-based heating system.	Experimental data with a DAQ system based on IoT sensors for the identification process.
F. Belic et al. [112]	2021	Demonstration of a simple implementation of a RC-network method for multi-zone buildings to save HVAC energy use.	The parameter identification effectiveness determined by simulation and experimental data obtained from the literature.
Joe [113]	2022	Application of MPC with a grey-box model to investigate the operational cost-savings potential of an underfloor air distribution system.	Experimental data used for the identification process and simulation-based case study to quantify the savings potential of the MPC.

3.3. Black-Box Modeling Approaches

With the rapid development of smart-integrated technologies (e.g., smart sensors and electric appliances), the data collection from various devices or HVAC-related systems in a building has become much easier [114]. Then, those collected data can be facilitated to improve the energy-efficient performance across multiple research fields with data mining techniques [115]. With such developments, the black-box modeling approach (i.e., the data-driven model) has recently gained much attention as one of the biggest, most promising building energy modeling techniques because of its simplicity and flexibility [116,117]. Unlike white-box and grey-box models, black-box modeling approaches do not require principle physical equations to predict thermal and energy behaviors in a building. A greater use of relatively complex HVAC controls and connected building energy systems, consisting of many subsystem configurations, is advancing the use of black-box modeling approaches and simulations. Black-box models for building thermal and energy prediction are generally developed based on historically measured or generated data to capture the hidden mathematical relationships between input and specified output variables using machine learning and statistical methods [118,119]. Figure 4 represents a general process of machine learning-based black-box modeling approaches. Black-box model approaches have been well adaptable for building HVAC-related applications without the need for detailed physical information about a building. Most projects for building HVAC applications focus on analyzing time-series datasets with training, validation, and testing steps [120].

The black-box modeling process involves several steps, including data collection, pre-processing, training, validation, and testing datasets to evaluate the implemented machine learning algorithms. For building HVAC system applications, various time-series data variables (e.g., data type, weather conditions, internal heat gain rates, schedules, and operation features of HVAC systems) could be included. A building's physical parameters (e.g., locations, the number of floors, window to wall ratios, and surface construction features) are also important for a cluster analysis based on data collection and pre-processing phases [119]. The black-box model is developed and run on the training dataset in the training process. The results are then compared to the original training data to adjust the different parameters of the algorithm to fit the training dataset [122]. The validation process is considered to tune key modeling parameters to improve the fitting accuracy of the implemented algorithm, which already fits the training dataset, using different datasets [120,123]. The testing process is conducted to evaluate the modeling and predicting performances by running the developed algorithm on the test dataset (e.g., the remaining part of the entire dataset) [120]. After the evaluation, any errors or uncertainty factors could be analyzed to capture practical issues with the model's development (e.g., model input/output parameters and structures), as shown in Figure 4.

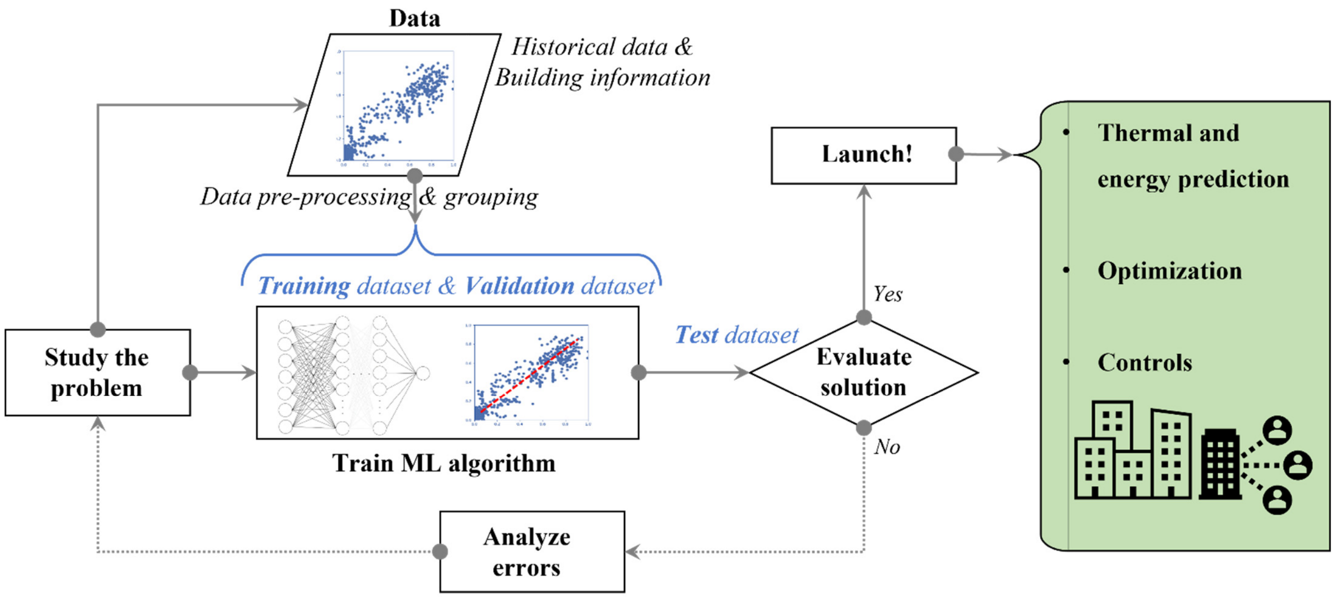

Figure 4. Schematic of a typical machine learning-based "black-box" model approach [121].

By reflecting the benefits of their classification and prediction capabilities, numerous modeling techniques have been developed and explored in the building domain for building thermal and energy predictions, fault detection and diagnosis, and building system optimization and controls [117,124]. Figure 5 lists the black-box modeling approaches for building systems' modeling and optimized controls. A review study by Afram and Janabi-Sharifi [117] provides a good overview of the data-driven modeling methods for HVAC modeling techniques in more detail. A taxonomy of the data-driven models is typically based on the criteria of a dataset for single-input/output or multiple-input/output structures while considering auto-tuning, the ability to model linear or nonlinear behaviors, and the robustness to parameters and disturbances [117,125]. Detailed information on each modeling algorithm can be found in the study [4,117]. Table 3 summarizes the representative papers regarding black-box modeling approaches, focusing on HVAC energy modeling techniques and practical applications. The modeling techniques and features presented in Table 3 are described based on the list of the representative black-box methods, as shown in Figure 5. Since this literature review is basically intended to present HVAC-related research and practical applications of three practical modeling approaches, the reviewed articles, listed in Table 1 through Table 3, are focused on specific tasks applied in building HVAC-related systems and their MPC fields based on a database search.

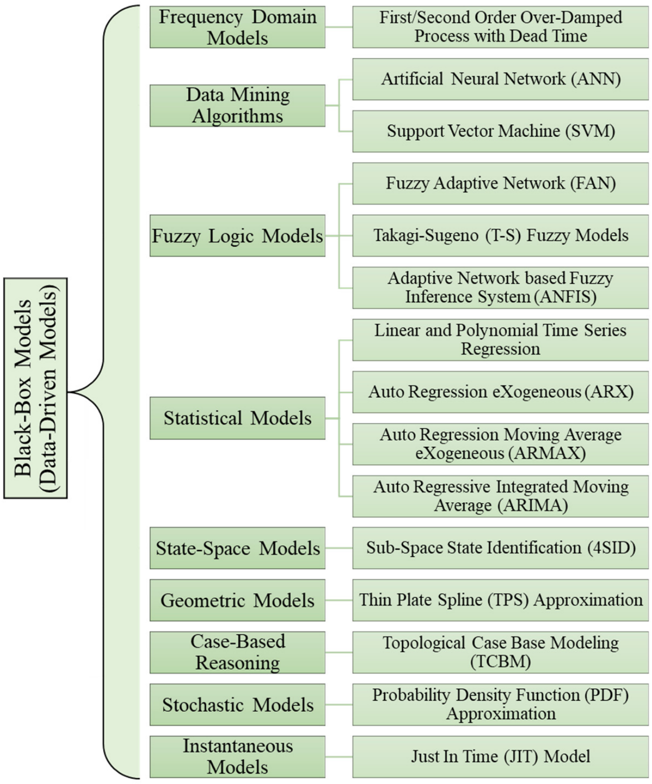

Figure 5. List of the representative "Black-box" modeling techniques, reprinted with permission from Ref. [117].

Table 3. List of the representative reviewed papers regarding "black-box" modeling approaches.

Source	Year	The Focus of Article (Objectives)	Modeling Techniques and Features
Fan et al. [126]	2014	A data mining-based approach for developing an ensemble model for predicting next-day energy consumption.	• Data mining algorithm: - The entropy-weighted k-means for clustering analysis; - The generalized extreme studentized deviate test for outlier detection; - Leave-group-out cross-validation for parameter optimization.
Jetcheva et al. [127]	2014	A building-level neural network model for day-ahead electric load forecasting.	• Data mining algorithm: - The k-means for clustering analysis; - Neural network (NN) for load forecasting; - SARIMA for the comparison with the NN.
Ma and Cheng [115]	2016	Development of an integrated data mining framework to estimate building EUI on an urban scale.	• Data mining algorithm: - Support vector regression (SVR), artificial neural network (ANN), and elastic net for elec. load forecasting and comparison; - The correlation feature selection (CFS) for a data filter method.
Zhang et al. [123]	2016	Development of the forecasting model using weighted SVR with nu-SVR and epsilon-SVR to predict time-series half-hourly and daily electricity consumption.	• Data mining algorithm: - Support vector regression (SVR); - DE, genetic algorithm (GA), and particle swarm optimization (PSO) for optimal parameter comparison.

Table 3. *Cont.*

Source	Year	The Focus of Article (Objectives)	Modeling Techniques and Features
Sarwar et al. [128]	2017	A field validation study of an autoregressive with an exogenous model for thermal load prediction.	• Statistical model: - An autoregressive with exogenous (ARX) for thermal load prediction and validation.
Keshtkar and Arzanpour [129]	2017	An adaptable autonomous energy management solution for the residential HVAC system control.	• Fuzzy logic model: - Supervised fuzzy logic model to detect, learn, and adapt to new data.
Homod [130]	2018	Development of a novel control algorithm that could handle large-scale nonlinear systems' uncertainty characteristics.	• Statistical model: - Nonlinear regression using Gauss–Newton method for fine-tuning operation; - Feedforward strategy to boost the stability of the system control.
Causone et al. [131]	2019	A data-driven procedure to create yearly occupancy and occupant-related electric load profiles for building energy simulation.	• Data mining algorithm: - A self-organizing map (SOM) and k-means for clustering analysis; - A K-NN algorithm for classification.
Png et al. [132]	2019	Implementation of a smart and scalable control approach (i.e., smart-token-based scheduling algorithm (Smart-TBSA)) using IoT devices and a machine learning method.	• Data mining algorithm: - Neural network (NN) for thermal load forecasting.
H. Moayedi et al. [133]	2019	Development and model validation of energy performance prediction models using machine learning techniques and measured data.	• Data mining algorithm: - Multi-layer perception regressor; - Lazy locally weighted learning; - Alternating model tree; - Random forest; - ElasticNet; - Radial basis function regression.
Ali et al. [134]	2020	A methodology to implement bottom-up, data-driven, and spatial modeling approaches for multi-scale geographic information system mapping of building energy modeling.	• Geometric model: - Geographic information system (GIS) mapping. • Fuzzy logic model: - Fuzzy string-matching algorithms. • Data mining algorithm: - Deep neural network (DNN) for building energy prediction.
Akbari-Dibavar et al. [135]	2020	A hybrid optimization model for smart home energy management in day-ahead and real-time energy control.	• Stochastic model: - Stochastic programming for uncertainty analysis; - A flexible, robust optimization approach to creating a tractable equivalent of the problem.
Tian et al. [136]	2020	An innovative method to develop energy-efficient building energy models in office buildings.	• Statistical model: - Statistical analysis to explore the relationship between features and energy consumption. • Data mining algorithm: - Shapley Additive exPlanations (SHAP) to quantify the impact of each outcome of a model.
Chiesa et al. [137]	2020	A working prototype of an IoT system that controls natural and artificial light balance for smart buildings.	• Fuzzy logic model: - Fuzzy control logic for a LED light controller.

Table 3. *Cont.*

Source	Year	The Focus of Article (Objectives)	Modeling Techniques and Features
M Borowski and K. Zwolinska [138]	2020	Development and model validation of cooling energy prediction models for a hotel building using two ML techniques: ANN and SVR.	• Data mining algorithm: - ANN; - SVR.
Kim et al. [139]	2021	Development of a new computational model that predicts the thermal load in HVAC&R to be handled by each device and equipment model.	• Data mining algorithm: - Artificial neural network (ANN) for HVAC flow rate prediction and performance.
Elkamel et al. [140]	2021	Development of the generation capacity schedules to meet the system's load ability using a personal rapid transit system.	• Stochastic model: - A stochastic mixed-integer linear programming model for day-ahead scheduling.
Sonta et al. [141]	2021	Methods for linking lighting zone energy to zone-level occupant dynamics and simulating energy consumption of a lighting system based on optimizing the layouts.	• Stochastic models: - A stochastic approach for occupant clustering; - Genetic algorithm for optimizing designs of buildings. • Statistical models for energy consumption prediction: - Support vector regression; - Multiple linear regression. • Data mining algorithm for energy consumption prediction: - Artificial neural network (ANN); - Random forests.
Chaouch et al. [142]	2021	A smart approach of the HVAC control system to reduce the energy consumption without affecting the thermal comfort of occupants.	• Fuzzy logic model: - The fuzzy logic for control rules.
Zhang [143]	2021	Development of a framework that integrates active learning and feature selection for MPC with data-driven building energy modeling improvement.	• Data mining algorithm: - Active learning algorithm in machine learning with feature selection for predictive control.
Geraldi et al. [144]	2022	A framework to reduce the uncertainty of archetypes for benchmarking buildings using entropy and cluster analysis.	• Data mining algorithm: - Artificial neural network (ANN) for building energy prediction; - The k-means for clustering analysis. • Statistical model for the target building stock's energy use analysis.
Zhou et al. [145]	2022	Development of a predictive energy management strategy for smart community, including water-based district cooling for a cluster of buildings' several electric vehicle charging stations.	• Stochastic model: - Scenario-based stochastic model for MPC using Modelica-based dynamic co-simulation model of smart community.
Hu et al. [146]	2022	Development of a data-driven urban building energy model synthesizing the solar-based building in tendency and spatio-temporal graph convolutional network algorithm.	• Geometric model: - Urban geographic model for capturing building level characteristics and weather data; - Graph neural network mapping model for predicting building energy consumption and quantifying the impact of interdependency on the energy use.
Wei et al. [147]	2022	A coupled real-time occupancy and equipment usage detection/recognition approach for efficient building energy controls of a smart building.	• Data mining algorithm: - Convolutional neural network (CNN) for building energy prediction; - Region-based CNN for object detection and recognition.

4. Model Predictive Control (MPC)

As the HVAC systems play a critical role in the energy consumption in buildings, appropriate capacity determination and efficient control methods are key aspects to reduce building energy consumption and, thus, environmental issues from the design stage to the operation stage [148]. Because the control strategy of the HVAC system is typically not optimized at the first phase in terms of the indoor cooling/heating load and relevant energy costs, it is relatively hard to satisfy the thermal comfort of occupants completely in the building's thermal zones. In this aspect, as a method for energy-efficient control, techniques such as MPC, which can predict the subsequent operation of the system and find an optimal control method through an optimal algorithm, should be applied to the HVAC system in buildings [149,150]. Figure 6 depicts a typical closed-loop MPC scheme for a building's applications. To implement an MPC scheme for building HVAC energy and connected systems, real building and energy modeling parts need to be considered with a control loop. The real building domain of the control loop consists of the actual building affected by real-time weather and the building's characteristic conditions, an estimated to provide the real-time state estimates and the input sequence from the MPC domain. In addition, the MPC domain consists of two major parts: (1) an optimization part and (2) a building energy simulation model. Various optimization and modeling techniques can be used for the MPC regarding features and applications of control strategies (e.g., control functions, parameters, and controllable components of energy systems in a building).

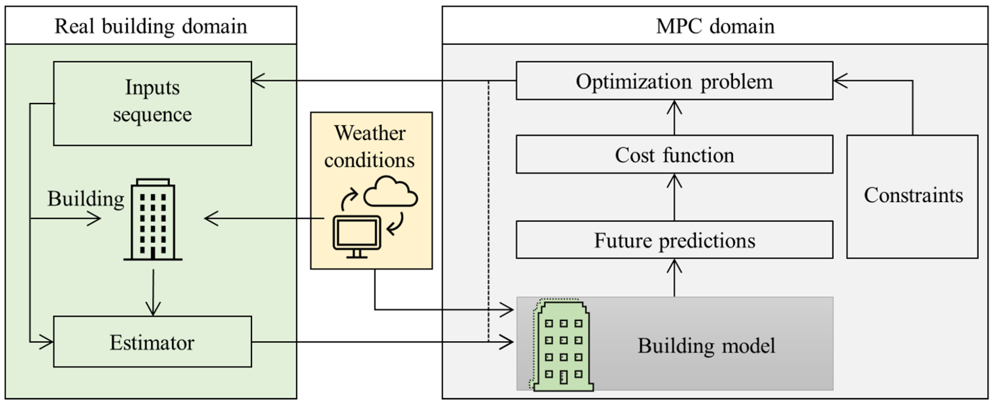

Figure 6. Schematic of the standard control-loop system for MPC-based building control, based on Ref. [21].

With such MPC frameworks, various studies have recently been conducted on HVAC systems and their related subsystem parts to enhance a building's energy-efficient performance. According to Gholam et al.'s [151] review study, the most predictive control application parts under the built environment were HVAC-related components, including air-handling units (AHUs) and different types of HVAC configurations to provide cooling and heating to the conditioned zones. Figure 7 illustrates the schematic of typical HVAC air-loop and water-loop configurations. This figure shows different components, including heating/cooling sources, condenser parts, air-terminal units, AHUs, and zonal supplementary systems. According to the study [15], there are two reasons why designing an HVAC controller appropriately is challenging and complex. This is mainly because there are not only many related subsystems associated with the HVAC system, but also control levels (e.g., target setpoint and actuator level) of each component that could be different, depending on the system's configuration. This review paper focuses on the MPC applications of the HVAC components: (1) radiant heating and cooling systems, (2) AHUs, (3) chiller and cooling tower parts, (4) and heat-pump-based HVAC systems.

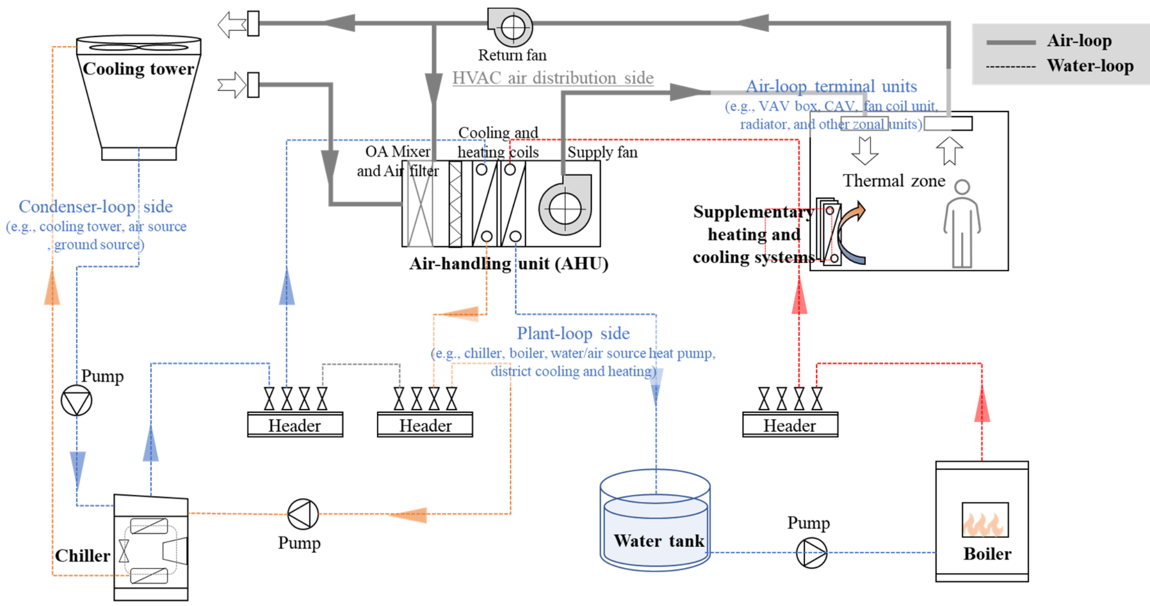

Figure 7. Schematic of typical HVAC air-loop and water-loop configuration.

In addition, most of the recent optimization studies on MPC techniques have focused on optimal control to save the HVAC system's energy and satisfy the occupants' thermal comfort [152]. Additionally, in the case of a building's HVAC energy analysis, there is a tendency to analyze it together with the energy cost (electricity charge, primary energy cost) [153]. Based on such observations, this section provides an overview of MPC-based HVAC operation methods and their practical applications based on published research papers.

4.1. Radiant Cooling and Heating Systems

For radiant cooling and heating systems, Woo [154] proposed a new MPC-based surface condensation prevention framework that can accurately estimate the rate of surface condensation for thermo-active building systems (TABS). MPC-based TABS achieved 21.0% to 29.6% of cooling distribution energy savings compared to the mechanical ventilation cooling system and 2.5% to 10.0% compared to the on/off control. Joe and Karava [155] show a smart operation strategy based on MPC and the results to optimize the performance of hydronic radiant floor systems. The MPC-based operation strategy confirmed 34% energy savings in the cooling season and 16% energy savings in the heating season compared to the feedback control. To compare energy savings and control performance, the proportional integral differential (PID), feedback, proportional-integral (PI), rule-based method, weather-compensated control, and heuristic feedforward control methods were introduced together, and the control performance was evaluated by comparing the time to reach the setpoint and the thermal comfort range. Zhang et al. [156,157] demonstrated control performance by implementing MPC in radiant floor cooling and combining it with underfloor ventilation (RFCUV), which was then compared with the PID. As a result of the comparison, the control performance (setpoint temperature adjusting time) was superior, the thermal comfort was satisfactory, and the energy-saving effects of 13.2~17.5% were confirmed. Bursill et al. [158] proposed and tested an MPC approach using rule extraction (RE), which can be simply applied to building controllers for optimal control. In their study, where MPC was implemented in 27 rooms of the building, they showed the energy savings of MPC and RE were 42% for MPC and 27% for RE during the cooling season, and 18% for MPC and 33% for RE during the heating season. In addition, the hybrid model predictive control (HMPC), distributed model predictive control (DMPC), and supervisory MPC were introduced and showed superior results than normal MPC. Siroky et al. [159] provide a good example of the HMPC application to a building heating system. Their hybrid model includes continuous variables that correspond to physical and discrete parameters serving as indices of a linear time-invariant model. Their proposed HMPC strategy enhances comfort and shows about 10.5% energy savings compared to the normal MPC.

4.2. Air-Handling Units (AHUs)

In a conventional HVAC system, the air-handling unit (AHU) is a challenging component to accomplish a satisfactory performance over the entire operating range by using linear control due to its nonlinear nature of system behavior. The representative role of MPC in the AHU is to propose a supply air temperature (SAT) that maintains appropriate energy consumption and an indoor environment above a certain level while maintaining a high level of control performance. Yang et al. [160] present a novel MPC developed for a dedicated outdoor air system (DOAS)-assisted separate sensible and latent cooling (SSLC) system. The MPC performance when controlling a conventional AHU system and a DOAS-integrated SSLC system was investigated experimentally and compared against a conventional feedback-control-based building management system (BMS). The comparison results show that the MPC system could achieve 18% and 20% savings in electricity for the single-coil AHU and DOAS-integrated SSLC, respectively. In addition, the thermal comfort can be improved significantly compared with the BMS. The DOAS-integrated SSLC turned out to be advantageous compared to the single-coil AHU as it produced a better thermal comfort when MPC controls both systems. Hadjiski et al. [161] discussed a thermal comfort-based MPC for a wooden house AHU. The optimization procedure was carried out in such a way as to minimize energy consumption, satisfying the predicted mean vote (PMV) and additional constraints. As a result, the proposed MPC supervisory control algorithm guarantees thermal comfort for occupants and energy efficiency. Since the existing control method has cost and energy efficiency limitations, MPC has been applied and studied as a method for this.

The biggest advantage of MPC technology is that it can optimize the system performance during changes in operational conditions and failures according to various situations through real-time measurement and prediction. Lee et al. [162] aimed to develop a control algorithm to run a typical VAV system with optimized AHU discharge air temperature (DAT) setpoints. In the study, the ANN proposes the hourly AHU DAT with the lowest total cooling energy consumption. The results showed that the predictive accuracy had a low coefficient of a variation root mean square error (CvRMSE) of 24%. In addition, the predictive control algorithm reduced the cooling energy by around 10%, compared to a typical control scheme of constantly maintaining AHU DAT at 14 °C. Henze et al. [163] demonstrate optimized control of a real-time building thermal storage inventory in a test facility based on a predictive model. The model-based predictive optimal controller effectively orchestrated all secondary and primary building mechanical systems in real-time without sacrificing the thermal comfort. It turned out that despite the imperfect weather forecasts and mismatch of predictive building energy predictions compared to the actual building energy, the measured utility cost savings were noticeable.

Most of the recent optimization studies conducted using the MPC technique in the AHU dealt with the system's energy savings and occupant's thermal comfort. Heuristics, PID, and PI were introduced together to compare energy savings and the control performance, and the control performance evaluation was also compared. Schwlngshackl et al. [164] dealt with the multi-input-multi-output (MIMO) control for an industrial AHU system. In their MIMO control, the temperature and relative humidity of the supply air are controlled simultaneously. The AHU cannot show satisfactory performance by using linear control due to its nonlinear behavior in the system characteristics. They proposed a MPC strategy based on a network of local linear models. The proposed network is compared against a conventional PI control, and its accuracy performance is demonstrated in both a simulation and a real-world test plant. The proposed idea can improve the plant's performance compared to the PI strategy. Huang et al. [165] demonstrated a MPC strategy to improve the control of the AHU discharge air temperature by dealing with the constraints and uncertainties directly. Their proposed method is evaluated in a dynamic simulation environment and compared with a conventional PI control. They showed that the proposed method provides improved robustness compared to the traditional PI control under a wide range of operating conditions. Huang [166] proposed a new control strategy for the thermal zone system to deal with uncertainties, constraints, and nonlinearities. In the study, a bilinear predictive controller is proposed for the zone temperature control and a gain-scheduled robust predictive controller for the damper control. The control capability of the proposed strategy was compared against the typical PI control. It turned out that under different operating conditions, the proposed method showed greater robustness. It also demonstrated that a good control capability could be accomplished without much user intervention and commissioning.

Some studies have been conducted in computer simulation environments, and some have explained the results of applying MPC to an actual building. EnergyPlus, TRNSYS, and SIMulator of Building And Devices (SIMBAD) are often used as building energy simulation programs, and MATLAB and LabVIEW are often used as programming software for MPC implementation in real applications. In addition to the conventional MPC, various MPC strategies, such as the supervisory MPC, economic MPC, centralized MPC, closed-loop MPC, linear time-varying MPC, successive linear MPC, and nonlinear MPC, were introduced in the literature [167–169]. Lee et al. [55] assessed the performance of the standing column well (SCW) heat pump integrated with the heat storage tank using EnergyPlus. To check the performance of the SCW system connected to the heat storage tank, PLRs, COP, and the energy requirements of the typical systems based on a window air-conditioner and boiler were evaluated. As a result of the study, the SCW heat pump system connected to the heat storage tank showed energy savings of about 62% annually compared to the conventional system and about 14% annually compared to the SCW heat pump without the heat storage tank. Moon [170] suggested an indoor temperature strategy method using ANN models for providing a comfortable thermal environment through the integrated control of the surface openings and the cooling system. The performance of the traditional- and ANN-based methods were comparatively evaluated for the double-skin-facade building using the TRNSYS and MATLAB software. It turned out that the proposed ANN-based logic could significantly reduce the number of operating condition changes of the surface openings and cooling system while improving indoor temperature conditions. However, the ANN-based control did not show superior energy efficiency compared to the conventional logic, and it increased the amount of heat removal by the cooling system.

4.3. Heat Pump-Based HVAC Systems

Most recent optimization studies conducted using the MPC technique for heat pumps focused on the energy saving-related aspects. In general, it is important to maintain a high COP of heat pump technologies for energy-efficient operations in building applications. In the case of a ground-source heat pump (GSHP), the energy consumption can be reduced by efficient heat exchange and thermal storage, and the loss of the geothermal heat source should be minimized. Various control strategies for heat pumps, e.g., the PID, genetic algorithm, rule-based control, and feedback control, have been introduced to analyze the performance or effect of the MPC application. The performance evaluation tends to be mainly carried out through a COP comparison. Kuboth et al. [171] investigate the potential of MPC for a heat pump in detached houses in terms of thermal comfort, electric energy, and photovoltaic energy self-consumption. The MPC for a heat pump is comparatively evaluated to a standard control strategy implemented into the reference test rig. Their results showed an average improvement of 22.2% on heat pump COP and 234.8% on photovoltaic energy consumption, and it also showed that a resulting average operational cost reduction of 34.0% can be achieved. Bechtel et al. [172] analyzed the impact of different heat pump powers and heat storage sizes on shifting potentials and cost savings. The parametric study results showed a significant improvement in energy efficiency and cost savings.

Furthermore, the limitations of considering variable electricity prices were investigated. Lee et al. [173] presented a realistic variable speed control optimization model for a heat pump using mixed-integer programming (MIP) to solve an issue with the unphysical characteristics of linear variable-speed heat pump (VSHP) models at low compressor speeds. MIP allowed for the consideration of all variables influencing VSHPs such as outdoor air temperature, indoor temperature, and compressor speed. This VSHP model was integrated with the neural network-based thermal load prediction in MPC simulations. It is shown that this strategy could decrease energy costs by 9–22% and carbon emissions by up to 22%. Weeratunge et al. [174] presented an MIP approach to minimize the operational cost of a solar-assisted GSHP system with a consideration of the time-of-use electricity price. Two system configurations and three operation modes were implemented and compared. It is shown that the thermal storage could improve the peak shaving, decreasing the need for expensive peak electricity production for the grid and decreasing operating costs by 7.8% when optimized for minimized cost. Wanjiru et al. [175] further developed an open-loop optimal control model using the closed-loop MPC for the operation of heat pump water heaters (HPWHs) and integrated renewable energy systems. The study showed that it could reduce 33.24% and 19l of energy and water in a day, respectively. The life cycle cost (LCC) analysis was also conducted, which showed that the payback period would be less than half of its life span.

4.4. Chillers and Cooling Towers

Chilled water systems are one of the commonly used systems in commercial buildings. Most recent optimization studies conducted using the MPC technique for chilled water systems focus on reducing cooling energy consumption. Optimal control studies were conducted on the related control variables such as chilled water temperature, condenser water temperature, chilled water flow rate, and condenser water flow rate. Yang et al. [160] presented an MPC developed for a dedicated outdoor air system (DOAS)-assisted separate sensible and latent cooling (SSLC) system. The MPC performance to control a conventional AHU system and a DOAS-integrated SSLC system was investigated experimentally and compared against a conventional feedback-control-based building management system (BMS). The comparison result showed that the MPC system could achieve 18% and 20% savings of electricity for the single-coil AHU and DOAS-integrated SSLC, respectively. In addition, they also showed that thermal comfort could be improved significantly when compared against the conventional feedback-control-based BMS. The DOAS-integrated SSLC turned out to be advantageous when compared against the single-coil AHU in producing a better thermal comfort when the MPC controls were applied to both systems. Kang et al. [176] constructed a predictive model of a DX AHU-water source VRF heat pump system based on EnergyPlus, MATLAB, and BCVTB. Performance curves and power consumption were calculated for the prediction of energy consumption. A sensitivity analysis of the cooling energy consumption was conducted based on the AHU discharge air temperature, refrigerant evaporative temperature, and condenser fluid temperature and flow rate.

In general, the goals for implementing the MPC's optimal control method are to keep the chiller's COP high and the indoor temperature at an appropriate level, resulting in improved energy consumption and cost. To analyze the performance and effect of MPC applications, various control strategies, such as the genetic algorithm, rule-based control, heuristic, fuzzy logic, adaptive neuro-fuzzy inference system, and feedback control, were introduced, and the performance evaluation was performed through a comparison of the COP, energy consumption, and operation cost. Lee et al. [177] developed a smart-valve-assisted predictive control to solve the problem of implementing artificial intelligence for energy savings in HVAC systems. Energy saving performances of the control system were tested, and the energy-saving effect showed around 30% across the test sites. Rossetti [178] investigated the idea of a "variable configuration" (VC) solar cooling plant that can self-tune its layout, adapt to different weather and user conditions, and guarantee maximum energy savings. Their parametric analysis showed the practical benefits of a VC plant coupled with an MPC controller. The primary energy ratio improvement of approximately 30% could be observed. In addition, research was conducted by predicting parameters using MPC and constructing an ANN-based model for MPC application. In addition, the general MPC, economic MPC, and model-free predictive control, which are extended from the basic MPC concept, were introduced in the references [160,176,179,180].

5. Conclusions and Discussion

With buildings responsible for a large portion of the global energy consumption and GHG emissions, improving energy efficiency is one of the most cost-effective ways to reduce energy usage and emissions in the building sector. Adopting high energy-efficient HVAC systems with advanced and optimized control and operation schemes can be effective solutions, and it is imperative to explore current research efforts to understand the current status and research gaps. This study reviewed the building energy modeling techniques and state-of-the-art updates for MPC HVAC applications towards reducing building energy consumption, costs, and the carbon footprint. This review study was based on the most recent research articles (e.g., from MDPI's and Elsevier's databases) in this field by classifying keywords and application types. For the review process, published search papers based on a scientific journal database search were classified into two main categories: (1) building energy modeling approaches and (2) model predictive control (MPC)-based optimization and operation. The relevant keywords of the research papers in each category were explored in detail, and then the overall methodologies and outcomes from the selected studies were investigated from different viewpoints. The key findings of this review study can be summarized as follows:

- The building energy modeling techniques are crucial steps in implementing the MPC-based control and operation schemes. There are three major categories typically used for building energy modeling approaches. There are no straightforward solutions because of the complexity and diversity of building HVAC system controls and/or operations. White-box modeling methods have been traditionally and widely used to assess building energy consumption and implement the MPC control schemes. Although the white-box modeling is relatively complex and time-consuming to obtain effective and accurate outcomes with realistic situations in a building, this approach is a powerful method to inform a building's HVAC control design, retrofit, and optimal operation. Based on the reviewed papers, it was identified that the co-simulation framework between simulation tools to overcome the disadvantages of each simulation modeling method provided more robust solutions in advanced HVAC control/operation technologies for current modern buildings under a non-stationary circumstance.
- The grey-box modeling approach has also been used for many buildings' HVAC and smart-connected system applications despite theoretical limitations, confusing model structures, and the need for parameter identification from measured data. This is mainly because this approach can be developed with relatively simplified physics-based calculation models and flexible and scalable applications. Therefore, it can also apply to multiple building simulations and grid-connected system levels. Based on the observations from the reviewed papers, the parameter identification, which is a necessary process for model development, varied according to different research and practical applications, with mostly experimental and/or simulation-based assumption identification being used. Lately, stochastic-based or uncertainty framework approaches have also been applied to grey-box models to develop more advanced network models, and thus, operate with dynamic control schemes.
- For the use of black-box models, many building energy researchers have adopted this method due to their capabilities to handle complex and nonlinear problems, specifically when complicated datasets from single/multiple HVAC systems and different control levels need to be considered. Since this method is based on a statistical analysis of field-measured data, data collection and pre-mining processes before the model

training/testing phases play a critical role in adjusting the model development conditions for a better performance. Because the most unified building energy simulation tools do not provide a black-box model analysis option, language-based (e.g., MATLAB, Python, and R) development is commonly considered based on the datasets, which can be obtained from measured and/or simulated data. Among the reviewed studies, the most frequently used data-mining algorithms were the k-means for clustering analysis and building thermal load and energy forecasting algorithms were based on support vector regression (SVR), artificial neural networks (ANNs), deep neural networks (DNNs), recurrent neural networks (RNNs), and tree- and regression-based models. In addition, time-series datasets were mostly reflected to implement machine learning algorithms for training and testing datasets. To enable advanced and optimized control schemes for HVAC systems, co-simulation options were actively adopted to allow for the strengths of the thermal load calculation and future energy and cost forecasting by controlling interactions and the data exchange dynamically.

- To minimize the HVAC energy consumption in the building and its connected systems, an advanced HVAC control/operation design using the MPC framework needs to be significantly considered by detecting the change points of the building's behaviors and adjusting to the more effective control signals. Some components and configurations can be applied to MPC-based building HVAC control schemes. For example, based on the observations from the reviewed papers, an air-loop distribution side included air-handling units and zonal units to control the supply air temperature and flow rate actively, as well as the room setpoint temperature with MPC actuators, including coils, an economizer, and supply fans. For the water-loop side of an HVAC system, condenser-loop and plant-loop sides could be considered for the MPC control design. The consider-loop tends to include a cooling tower, air/water source, and ground source, whereas the plant-loop can consist of chillers, boilers, heat-pump-based HVAC, and district cooling/heating systems. The most frequently used actuators for such sides were fan and pump speeds for a condenser and supply water/refrigerant flow temperatures and rates. Based on the reviewed papers, co-simulation frameworks between a white-box model and a grey-box or a black-box model were typically considered to implement optimized MPC control schemes to minimize HVAC energy and costs.

Recently, the trends of affordable hardware costs, high-performance computing techniques, bit-data-based machine learning analyses, and the rapid development of IoT devices have practically led to an updated phase of the MPC-based HVAC applications. In future works, MPC techniques will be a key solution to implement the digital twins of smart homes and buildings in response to the growing energy and environmental issues globally.

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Nomenclature

Abbreviation

AHU	air-handling unit
ANN	artificial neural network
ARX	autoregressive with exogenous
ASHRAE	the American Society of Heating, Refrigerating and Air-Conditioning Engineers
BAS	building automation system
BCVTB	building control virtual testbed
BMS	building management system
CFS	correlation feature selection
CNN	convolutional neural network
COP	coefficient of performance
CvRMSE	coefficient of variation root mean square error
DAT	discharge air temperature
DNN	deep neural network
DOAS	dedicated outdoor air system
DX	direct expansion
ECBCS	energy conservation in building and community system
EIA	energy information administration
EUI	energy use intensity
FMI	functional mock-up interface
FMU	functional mock-up unit
GA	genetic algorithm
GHG	greenhouse gas
GIS	geographic information system
GSHP	ground-source heat pump
HMOC	hybrid model predictive control
HPWH	heat pump water heater
HVAC	heating, ventilation, and air-conditioning
LCC	life cycle cost
LTI	linear time-invariant
MDPI	Multidisciplinary Digital Publishing Institute
MIMO	multi-input multi-output
MIP	mixed-integer programming
MPC	model predictive control
PI	proportional integral
PID	proportional integral differential
PLR	part load ratio
PSO	particle swarm optimization
RC	resistance-capacitance
RE	rule extraction
RFCUV	radiant floor cooling combined with underfloor ventilation
SAT	supply air temperature
SCW	standing column well
SHAP	Shapley Additive exPlanations
SIMBAD	simulator of building and devices
SOM	self-organizing map
SSLC	separate sensible and latent cooling
SVR	support vector regression
TABS	thermo-active building system
TES	thermal energy storage
VAV	variable air volume
VSHP	variable-speed heat pump

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