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Review

A Critical Perspective on Current Research Trends in Building Operation: Pressing Challenges and Promising Opportunities

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Abstract: Despite the development of increasingly efficient technologies and the ever-growing amount of available data from Building Automation Systems (BAS) and connected devices, buildings are still far from reaching their performance potential due to inadequate controls and suboptimal operation sequences. Advanced control methods such as model-based controls or model-based predictive controls (MPC) are widely acknowledged as effective solutions for improving building operation. Although they have been well-investigated in the past, their widespread adoption has yet to be reached. Based on our experience in this field, this paper aims to provide a broader perspective on research trends on advanced controls in the built environment to researchers and practitioners, as well as to newcomers in the field. Pressing challenges are explored, such as inefficient local controls (which must be addressed in priority) and data availability and quality (not as good as expected, despite the advent of the digital era). Other major hurdles that slow down the large-scale adoption of advanced controls include communication issues with BAS and lack of guidelines and standards tailored for controls. To encourage their uptake, cost-effective solutions and successful case studies are required, which need to be further supported by better training and engagement between the industry and research communities. This paper also discusses promising opportunities: while building modelling is already playing a critical role, data-driven methods and data analytics are becoming a popular option to improve buildings controls. High-performance local and supervisory controls have emerged as promising solutions. Energy flexibility appears instrumental in achieving decarbonization targets in the built environment.

Keywords: advanced controls; data analytics; decarbonization; flexibility; model predictive control; building operation

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1. Introduction

1.1. Energy Context in the Built Environment

Buildings are major energy end-users and are responsible for 40% of the world's total energy consumption, 60% of the world's electricity, and 30% of greenhouse gas (GHG) emissions [1]. Despite initiatives targeting energy efficiency, energy use is expected to further increase in the future as a result of the combined impact of economic development and the change in consumption patterns, as well as an increase in the world's population projected to rise from 7.6 billion in 2019 up to 9.7 billion by 2050 [2]. In Canada, the residential sector and the commercial and institutional buildings sector account for 13% and 12% of the country's end-use demand, respectively [3]. Ongoing initiatives to electrify buildings aim to reduce GHG emissions by 40–45% in 2030 compared to 2005 and become net-zero by 2050 [4]. As a result of these developments and other trends, Canada's total electricity demand is projected to increase by 47% in 2050 compared to 2021 levels [5], thus presenting daunting challenges to the current and projected electric grid infrastructure. Buildings could play a pivotal role in addressing these challenges.

The main energy usage in buildings corresponds to heating, ventilation, and air conditioning (HVAC); along with domestic hot water, these account for around 50% of building energy end-use, the rest being shared with cooking, lighting, and other equipment (appliances, other plug-in devices) [6]. Space cooling currently represents only around 6% of the total building energy demand; however, cooling energy is projected to increase considerably and may become the primary energy usage in buildings [2].

Furthermore, buildings existing today will represent 70% of the Canadian building stock in 2050 [7]. Therefore, apart from new high-performance buildings, it is also critical to tackle existing buildings' issues through major design and controls retrofits.

1.2. Current Controls in Buildings

Traditionally, buildings have been controlled considering the comfort of their occupants as the primary goal. Therefore, sensors have been installed mainly to ensure that indoor environment quality requirements (temperature, humidity, air quality, etc.) are satisfied, not necessarily considering energy efficiency. However, given the increasing importance of the energy context, efforts have been made to improve the operation of buildings to reduce energy use and related costs while satisfying indoor environmental quality (such as thermal comfort).

The operational data commonly available in commercial and institutional buildings are collected from metering devices installed in critical locations of the HVAC system. These data might include temperature, relative humidity, pressure, flow rate, valve positions, damper openings, equipment on/off and modulation, current readings, lighting, and occupancy levels. All this information can be used by the Building Automation System (BAS) for local controls to guarantee satisfactory indoor environment quality while reducing energy usage. However, local controls have been generally developed to optimize the operation of pieces of equipment, not necessarily to optimize performance at the system level. A new generation of tools has emerged to leverage available building data to further improve building performance and reduce energy usage, such as Building Energy Management Systems (BEMS) [8,9] or Energy Management and Information Systems (EMIS) with more advanced capabilities [10,11]:

- Energy Information Systems (EIS) targeting performance tracking;
- Fault Detection and Diagnostic (FDD);
- Automated System Optimization (ASO).

From an energy efficiency perspective, buildings commonly perform beneath their potential: unfortunately, as long as thermal comfort is met, inefficient operation often goes undetected. Improving building controls, such as introducing better control sequences or correcting inefficiencies, could help reduce a building's annual energy use by up to 30% [12], electric peak loads by up to 20% [12], and maintenance costs by 20% [13]. Recommissioning and ongoing commissioning initiatives have emerged to bridge the gap between design and in-operation performance. They could yield 5–15% annual energy savings with typical payback periods lower than 3 years [14]. Fault detection and diagnostic tools become critical in this context to detect and correct inefficiencies when they occur. Several commercial products that are available on the market address the optimization of building operations and controls [15]. The majority focus on EIS and FDD tools, and only a few of them target ASO [10]. These tools could provide energy savings of up to 9% on average while being cost-effective with a return on investment of less than 2 years [10].

Buildings are smoothly transitioning towards data-centric operations with an increased utilization of sub-hourly data and artificial intelligence (AI) techniques, as well as a focus on occupants and sustainability objectives. This paradigm shift is similar to that undergone by many industry sectors with the concepts of Industry 4.0 [16] and Industry 5.0 [17]. However, significant work remains to be achieved to accomplish such a shift.

1.3. Paper Objective

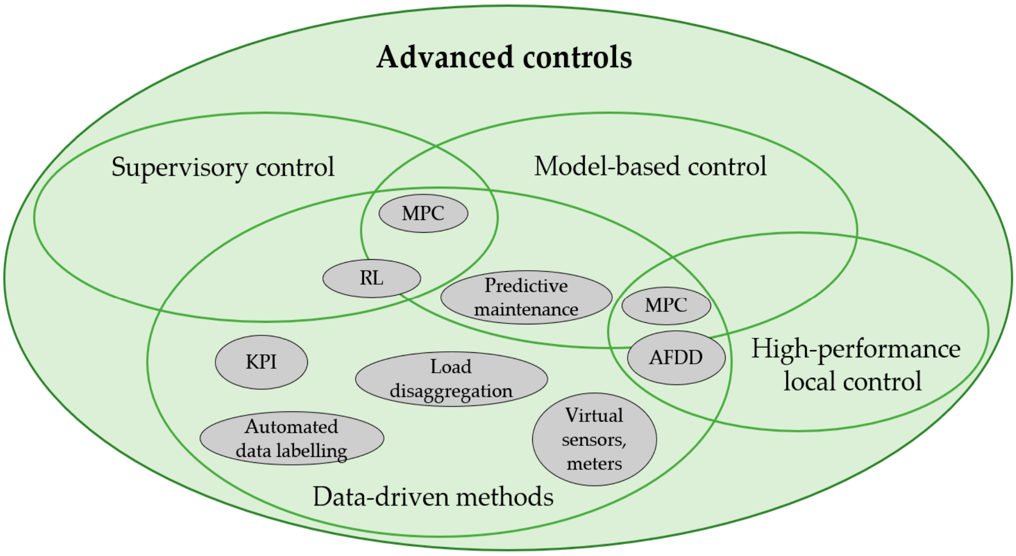
Within this context, the existing research has focused on different pathways to further increase building performance through better controls. However, significant practical hurdles (inefficient local controls, low data availability and quality, communication issues, etc.) are encountered when attempting to deploy the findings of advanced control research; this factor has slowed down their widespread adoption by building owners and operators. This paper aims to provide a critical perspective on current challenges of advanced controls in commercial and institutional buildings and to explore opportunities that promise groundbreaking solutions for controls in the built environment.

Previous initiatives have tackled similar topics, but the focus was rather on specific applications: metadata schemas [18], data analytics [19], FDD [20], model-based predictive controls (MPC) [9,21–23], reinforcement learning [24], occupant-centric controls (OCC) [25,26], predictive maintenance [27], peak load management [28], building energy flexibility [29], strategies for building energy management systems (including MPC, demand side management, optimization, and FDD) [8], and data-driven building operations (with a focus on metadata, FDD, OCC, key performance indicators, virtual energy meters, and load disaggregation) [30]. Some other work emphasized the perspectives, challenges, and opportunities but also concentrated on specific aspects: industry engagement [31], data requirements for MPC [32], reinforcement learning [33], and OCC [34]. In this paper, the objective is to provide a broader overview of research trends on advanced controls in the built environment with a focus on practical considerations such as challenges faced to deploy advanced controls and opportunities to facilitate their adoption.

It is not the intent of the authors to provide an exhaustive review of the vast field of building operation nor to dive into technical details in one specific application. Rather, the content and structure of this perspective paper builds upon the authors' experience and personal assessment to shed light on current challenges and future directions in building operation research at a higher level. Each topic is based on recent state-of-the-art publications, preferably review papers, which were found through conventional channels (e.g., search engines such as ScienceDirect, MDPI, Google Scholar, and ResearchGate) and appropriate keyword searching. A large variety of keywords were used in combination with one another using Boolean operators ("and", "or"); some examples are "buildings", "control-oriented models", "data-driven", "data labelling", "energy flexibility", "fault detection and diagnostics", "key performance indicators", "load disaggregation", "metadata", "modelling", "occupancy", "predictive control", "reinforcement learning", and "virtual energy meters". Some of the material presented was inspired by fruitful discussions in workshops and conferences with colleagues, collaborators, and peer researchers.

1.4. Scope

In this paper, we focus on advanced controls that are seen as a means towards better building performance (energy usage, costs, peak demand, etc.) through improved operation. Advanced controls in this paper refer to various techniques and tools that could help improve the way current controls are designed. Figure 1 shows a conceptual diagram of what we considered "advanced controls" in this study. It includes both supervisory and local controls, as well as data-driven and model-based controls. We do not intend to provide a new definition of advanced controls, but rather to delimit the scope of the paper.



AFDD = Automated Fault Detection and Diagnosis; KPI = Key Performance Indicator; MPC = Model Predictive Control; RL = Reinforcement Learning

Figure 1. Conceptual diagram of what we consider as advanced controls in this study; applications in grey are discussed in this article.

Figure 2 complements Figure 1 by providing a word-cloud of research papers reviewed in this article; titles and abstracts were used for this purpose.

Figure 2. Word-cloud plots based on titles and abstracts of research papers reviewed in this article.

Finally, Abbreviations provides a list of the abbreviations that have been used throughout the paper for better readability.

2. Pressing Challenges

This section tackles challenges related to advanced controls in the built environment, specifically (in no particular order) local control inefficiencies, data availability and quality, communication issues, the need for guidelines and standards, the need for successful case studies and cost-effective solution sets, and insufficient engagement and training. These challenges are summarized in Figure 3 and discussed in detail in the corresponding subsections.

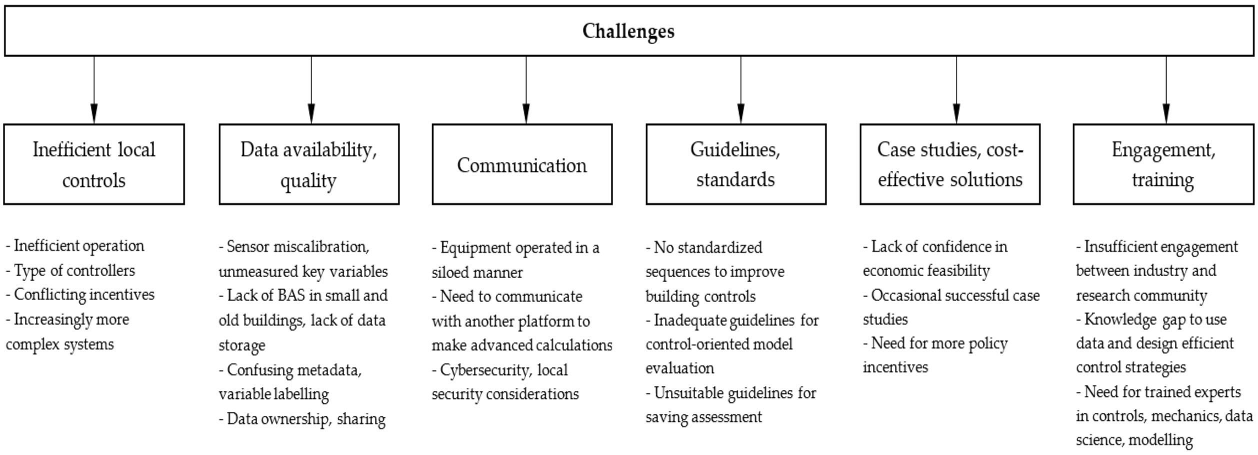


Figure 3. Challenges related to advanced controls in the built environment.

2.1. Inefficient Local Controls

2.1.1. Causes of Inefficient Local Controls

One of the main challenges for deploying advanced controls is the inefficient local controls currently seen in many buildings, which can be caused by various reasons.

- **Lack of simple energy-efficient control rules**: some buildings are still operated without simple energy-efficient control rules such as night setback of indoor air temperature in winter and air or water temperature reset strategies due to a lack of awareness, training, or time of building operators; a compelling example of such inefficiencies has been provided by Gunay et al. [35] for 14 office buildings.
- **Faulty operation and performance degradation**: inefficient operation could also be caused by performance degradation with time [27], faulty operation, or low-efficiency operation, although no fault has been detected.
- **Suboptimal electric power management**: better managing building electric power is also a key aspect for current and future operations and some buildings still show significant differences between average electric load and peak load, which can be costly when the utility rate depends on total energy use and peak power demand [36].
- **Inadequate occupant-centric controls**: occupancy is also a key aspect that affects building performance. Most buildings are generally operated based on full occupancy, for instance, to determine fresh air requirements; however, the actual occupancy of commercial buildings rarely exceeds 50% [30], unlocking energy efficiency opportunities (e.g., lower air-change per hour). Moreover, occupancy can show strong variability, especially with the rise of telework practices since the beginning of the COVID-19 pandemic.

Any new advanced control projects targeting the implementation of advanced control algorithms, such as model-based predictive controls, might need to tackle these issues first before adding another complexity layer with supervisory controls. Recommissioning, ongoing commissioning, and predictive maintenance generally address simple energy-efficient control rules, faulty operation, and performance degradation with time. FDD algorithms are typically used to detect and diagnose such inefficient behaviour to provide corrective actions. Hard faults consist of physical failure of mechanical equipment such as sensors and actuators (stuck, leaks, broken components, fouling) whereas soft faults are related to controller tuning errors, programming mistakes, poor installation, and non-optimal commissioning [37].

2.1.2. Type of Controllers

Another aspect that slows down the deployment of advanced controls is the type of controllers. While DDC controls are suitable for advanced controls, a significant number of buildings—generally relatively old—still have pneumatic controllers [38], which limits the amount of available operational data and allows less flexibility for control modifications. On a related topic, the current infrastructure of existing building control platforms might show significant flaws and may not necessarily enable the integration of complex control algorithms [39]. The deployment of recent research in advanced controls then becomes laborious.

2.1.3. Conflicting Incentives

Although a building could operate in fault-free modes, lessons learned from previous projects showed us that conflicting incentives could also affect the performance of the building. When a building participates in a utility's demand response program or is operated in the context of peak power demand charge, a dual-fuel hydronic heating system (i.e., electric and gas boilers) could favour the operation of gas boilers, although less efficient, at the expense of the electric boiler, leading to a significant increase in GHG emissions locally. Increasing ventilation in the context of COVID-19 is another compelling example. While essential to reduce the spread of SARS-CoV-2 in closed environments, ventilation might have been increased more than necessary [40]. Awad et al. [41] investigated the implications of COVID-19 for electricity use in 27 government buildings. They found that peak loads were reduced in almost all buildings; nonetheless, the average base load was increased in 43% of buildings as a possible consequence of increased ventilation. Overall, the change in annual energy use varied between −33% and +25%.

2.1.4. Complex Integrated Energy Systems

Finally, buildings are being increasingly equipped with even more complex HVAC systems (e.g., heat pumps) and systems for on-site energy generation from renewable sources (e.g., photovoltaic) and for energy storage, either electrical (e.g., battery) or thermal (e.g., water tanks, ice banks). These buildings require sophisticated controls to optimally coordinate their operation and maximize operating efficiency and energy savings.

2.2. Data Availability and Quality Issues

2.2.1. Challenges Related to Data Availability and Quality

Sub-hourly operational data have become increasingly available in commercial and institutional buildings and represent an untapped opportunity to help better manage and operate buildings. However, this comes along with several challenges related to availability and quality:

- Sensors are not often recalibrated.
- Lack of submetering such as equipment electric current (fans, pumps), CO_2, and occupancy sensors, while some key variables might not be measured or directly available (e.g., critical temperatures, flow rates, etc.).
- Installing new sensors is relatively costly and involves practical issues such as installation, maintenance, and recalibration [42].

Since instrumentation has primarily been installed for monitoring and control purposes (not so much for energy efficiency), there is also a lack of submetering or tools to determine how the energy is used in the building [30]. Such information could help provide electric and thermal energy use breakdown in buildings to understand where the energy is used and where advanced controls and energy conservation measures could have more impact.

2.2.2. BAS for Small and Medium Commercial Buildings

Building automation systems generally record data in large commercial buildings where building operation is complex and needs to be automated appropriately to avoid excessive costs. Such an infrastructure allows for the gathering of fine-grained operational data at sub-hourly intervals. In contrast, these data are generally less likely to be available in small commercial buildings since they are under-served by energy conservation tools, given their dispersion and lower payback potential. Small and medium commercial buildings (<50,000 ft^2) account for 94% of commercial buildings in the United States, 50% of commercial floorspace, and 44% of energy consumption, but only 13% have a BAS compared to 71% in larger buildings [43]. Similarly, older buildings with pneumatic controls not only offer less flexibility for controls modifications but also provide fewer operational data, thus severely limiting advanced control opportunities.

2.2.3. Data Storage

In BAS, operational data are generally collected and saved in trend logs for a few hours or a few days, but not in the long term. In this case, data storage devices must be installed, which could be costly. Although this additional cost enables the usage of data analytics tools, building owners might be reluctant to install such storage devices if the benefits are not clear. The notion of *data warehouses* and, more recently, *data lakes* have emerged in the past decades [44,45] as long-term data storage and management solutions. Building data are generally stored in a data warehouse, which is a large repository where data are stored in a well-structured manner and used for decision-making through data analytics [45]. With the increasing amount of available data from various sources, data lakes have appeared as centralized storage repositories, enabling the storage of raw, unprocessed data, including unstructured, semi-structured, or structured data [45]. Although different in terms of structure, both data warehouses and data lakes aim to support decision-making through data analytics, visualization, and machine learning.

2.2.4. Metadata and Variable Labelling

Another important issue with operational data in buildings is metadata management and variable labelling, which slows down the large-scale deployment of data analytics tools and advanced controls. Hard-coded names, which are prone to inconsistencies and mistakes, are still mainstream in most existing buildings. The description of control points is generally of poor quality in terms of consistency, completeness, and usefulness, while it does not follow any standards and heavily depends on control solution vendors and technicians [30,46]. There have been several initiatives to tackle metadata schemas and ontologies [18], and a few have emerged as potential solutions, such as

- Haystack schema [47];
- Brick schema [48];
- Google Digital Building ontology [18];
- Real Estate Core and Smart applications reference ontology (SAREF) [18].

Work is still required to provide a unified approach for data semantic information. ASHRAE Standard 223P is a step in this direction [49].

2.2.5. Data Ownership and Data Sharing

Finally, the question of data ownership and data sharing is becoming more and more prevalent. Since several users could benefit from building operational data (the building owner, the building occupants, the service provider, or the utility), the question of "who owns the data?" remains. Ecobee, a Canadian home automation company, proposed a volunteer-based solution to this issue with the "Donate Your Data" program [50] and made available the smart thermostat data of over 10,000 anonymized residential buildings for research purposes [51,52]. However, this approach might be more difficult to deploy in commercial and institutional buildings. Building owners might not want to share the data due to potential security and privacy issues, but they might want to know what benefits they could get by sharing the data. Nonetheless, initiatives exist, such as the collection of sub-hourly measurement datasets of six real buildings for advanced control applications for energy use and indoor climate research purposes [53] or the Real Time Energy Management (RTEM) Incentive Program supported by New York State Energy Research and Development Authority (NYSERDA) [54], which allowed to make available operational data from over 200 commercial and institutional buildings in New York State [55]. Jin et al. [56] have also collected detailed information about 33 open datasets of city-level building energy use from eight countries. Data granularity varies from 1 year down to 15 min and information includes energy use intensity or electricity consumption, among others. Similarly, Li et al. [29] have identified 16 building datasets suitable for building-demand responses or building-to-grid services that are based on real operational data, hardware-in-the-loop setups, and numerical simulations.

2.3. Inadequate Communication with the Control System

2.3.1. BAS Design in Siloed Manner

One key issue slowing down the massive deployment of advanced controls is inadequate communication with the control system. Current BAS have been designed in a siloed manner, where each subsystem (HVAC, lighting, security, power, etc.) intends to improve its performance independently; however, they usually compete with each other and there is a need for optimizing all the systems at the same time [39]. Master controllers could be used for this purpose to provide the main operational direction (e.g., perform building preheating) while letting local controllers adjust their operations accordingly. Data from other sources (e.g., occupancy sensors, electric vehicle chargers) that are not directly integrated into the BAS or control algorithms add another layer of complexity to operating buildings.

2.3.2. BAS Control and Computational Capabilities

Current BAS have also been designed to deal with simple if-then rules, but not necessarily to support advanced calculations based on a large amount of operational data to train computationally intensive artificial intelligence models or to run optimization routines frequently, whereas software tools (e.g., Matlab R2023a, Python 3.8.8, R 4.2.1) could be quite powerful for such purposes. To enhance computational ability and resources, cloud and edge computing techniques could be leveraged. Additional communication infrastructure might thus be required to exploit the capabilities of current BAS for controlling buildings, along with the capabilities of more advanced data analytic tools for handling large amounts of data, building complex models, and optimization routines. This might complexify the communication between the BAS and the advanced calculations modules, which could physically be hosted in a workstation, in the same local network as a workstation, or in the cloud. Moreover, different communication protocols (e.g., BACnet, Modbus, LonWorks) may be used by different devices, which creates barriers to interoperability.

2.3.3. Cybersecurity

Finally, lessons learned from previous projects showed us that security considerations must be included during the design of advanced controls and should be addressed sooner rather than later, such as the existence of a firewall or VPN. Cybersecurity has become an increasing concern for smart connected buildings, especially for cloud-based tools. In contrast, some buildings could show particularly stringent security restrictions such as no access to the internet, which could make access to weather forecasts (for instance) and cloud computing more cumbersome.

2.4. Lack of Guidelines and Standards

2.4.1. Buildings Controls Improvement

In addition to previous challenges, more guidelines, standards, and codes tailored for control applications are needed. For instance, there is a lack of guidelines to improve building controls. The initiative of ASHRAE Guideline 36 (G36) [57], although primarily U.S. focused and not necessarily applicable to cold climates, aims to provide a recipe for high-performance sequences for local controls for air-side systems (mainly variable air volume systems and terminal units) but also for water-side systems.

2.4.2. Model Accuracy Assessment

Advanced control strategies such as predictive control might also take advantage of control-oriented models to make informed decisions and provide optimal operation recommendations or to directly operate the building. However, there are no model accuracy assessment guidelines specifically tailored for controls. ASHRAE Guideline 14 [58] provides calibration criteria for physics-based energy simulation models using hourly simulation time steps; a model can be considered calibrated if the coefficient of determination (R2) is higher than 0.75, the normalized mean bias error (NMBE) is lower than 10%, and the coefficient of variation of the root mean square error (CV-RMSE) is lower than 30% [59]. Such numbers generally apply to main energy or temperature variables (e.g., electricity use, gas consumption, indoor air temperature) and provide a reasonable gauge for the evaluation of control-oriented model accuracy. Nonetheless, other aspects specific to controls should also be addressed:

- The applicability to other types of variables: fan power, electric boiler power, electric baseload;
- The impact of sensor uncertainty and data quality [60];
- The robustness to extrapolation, especially for black-box models, which are purely data-driven models; this aspect is further discussed in Section 3.1.

2.4.3. Savings Assessment

There is also a lack of guidelines about the assessment of savings following the implementation of advanced control strategies. The International Performance Measurement and Verification Protocol (IPMVP) [61] prescribes four principles for energy savings evaluations, yet it remains a question of how these principles could be applied to advanced controls due to the lack of detailed guides. Signature models for energy, cost, and thermal comfort could be developed based on sub-hourly to hourly [62], daily [63–66], and monthly [67] behaviours, but there are also other options, such as alternating operations between reference and advanced controls, and then comparing the two scenarios [68]. Research initiatives investigating the level of complexity required for the benchmarking model (from linear regression to advanced machine learning models) can also be reported, such as in [69].

2.5. Lack of Successful Case Studies and Cost-Effective Solutions

2.5.1. Economic Feasibility of Advanced Controls

One of the key barriers to the adoption of advanced controls lies in the economic feasibility of such solutions and the market awareness and confidence in realizing cost benefits. It is worth mentioning that the economic feasibility of advanced controls significantly depends on the current building operation. As discussed in Section 2.1.1, if the original strategy shows several inefficiencies or flaws, the new strategy will most likely provide more savings and be more cost-effective; conversely, an already well-operated building will show lower savings with advanced controls. This observation makes the expected performance difficult to estimate, whereas savings generated with a similar control strategy could greatly vary from one building to another.

The Smart Buildings Analytics Campaign [10] was organized in this context to prove the business case for building analytics: 85 software tools from 40 different EMIS vendors have been installed in more than 6500 buildings from 9 different market sectors and 104 commercial organization across the U.S. After two years of EMIS installation, they estimated energy savings (whole building level, for all fuels) and found [10,70]:

- **EIS tools**: savings ranging from −15% to 22% with a median of 3% and a top quartile (best practice) of 11–22%.
- **FDD tools**: savings ranging from 1% to 28% with a median of 9% and a top quartile (best practice) of 15–28%.

For both EIS and FDD, the simple payback period is 2 years. Results were not reported for ASO since it was not prevalent in the study with only two participants [10]. However, estimated savings can still be found in the literature for ASO: energy savings of 0–11% and payback lower than 6.5 years [10,71]. Despite these initiatives, the increasing amount of solution providers and the difficulty in distinguishing the differences between them slow down their adoption; a primer built upon the Smart Buildings Analytics Campaign has been designed to help owners better plan and use EMIS tools [70].

At the research level, advanced controls such as predictive controls have been widely investigated at the simulation level, but practical implementation remains relatively rare. Some model-based predictive control field demonstrations were reviewed in [72]. Energy savings greatly vary from one study to another, with values ranging from 4–7% up to 70%, with an average of 26% in reported results. Similar numbers were obtained for cost savings, whereas demand cost could reach up to 10–30%. Thermal comfort was also improved when reported. It is worth mentioning that the cost-effectiveness of advanced control strategies is always related to the original control strategy.

2.5.2. Policy Drivers

There is also a need for more policy incentives to encourage the deployment of advanced controls and intelligent buildings, even though some initiatives are noticeable. Requiring advanced controls in building certification programs could accelerate the widespread adoption of such tools. A *Smart Readiness Index* (SRI) is a standard scheme developed in the European Union for rating a building's ability to adopt smart technologies and services [73]. Successful case studies could provide solid foundations for the energy and economic benefits of advanced controls, which could foster their inclusion in building codes. Targets and mandatory reporting for building energy use and GHG emissions could also be policy drivers, such as the local law 97 in New York City [74], which sets carbon emissions caps for most buildings over 25,000 ft^2, starting in 2024 and becoming increasingly stringent over time (40% emission reduction by 2030, 80% by 2050).

2.6. Lack of Engagement and Training

2.6.1. Engagement between Industry and Research

The deployment of advanced controls requires industry engagement. There is a broad consensus that academic researchers and industry practitioners need to be more engaged with each other [31]; this observation applies to the building industry but also to other fields. Samad et al. [31] conducted a survey to evaluate industry engagement and perceptions regarding control research; the authors emphasized the value of rudimentary control research to facilitate industry uptake, even though advanced control technologies such as data analytics, fault detection and diagnosis, and model predictive control are perceived by practitioners as potentially impactful soon. They also mentioned that it is not necessarily in the company's best interest to publish the implementation of control because of confidentiality issues or the lack of incentives for dissemination; this lack of transparency makes the adoption of advanced controls more difficult to track.

2.6.2. Operators' Training

Even though building operators are willing to optimize building operations and are aware of potential savings, they generally lack the time to spend on such an activity. They also lack the knowledge on how to deploy energy-efficient control strategies and how to efficiently leverage operational data and control-oriented models to improve building performance. Data analytics, modelling, and control optimization could provide insights into building operation, but such tools require adequate training to be correctly used.

The development of advanced controls in buildings combines system knowledge with advanced data analytic methods and advanced modelling techniques. Control company employees often have a background in electrical engineering in general but not necessarily in HVAC or mechanical systems. With the advent of the digital age, data-driven approaches based on analytics and modelling will also become predominant and a general understanding of these concepts will become a must-have. Therefore, there is a need for trained experts not only in the field of controls and mechanical systems but also in data science and modelling. Industry can play a critical role along with academia in making newly graduated building technicians, operators, engineers, and researchers more employable and valuable in a fast-evolving, technology-driven world [31].

3. Promising Opportunities

This section discusses promising opportunities related to advanced controls in the built environment, namely, building models, data-driven and data analytics methods, high-performance local controls and advanced supervisory controls, and decarbonization through flexibility. They are shown in Figure 4 and are discussed in the corresponding subsections.

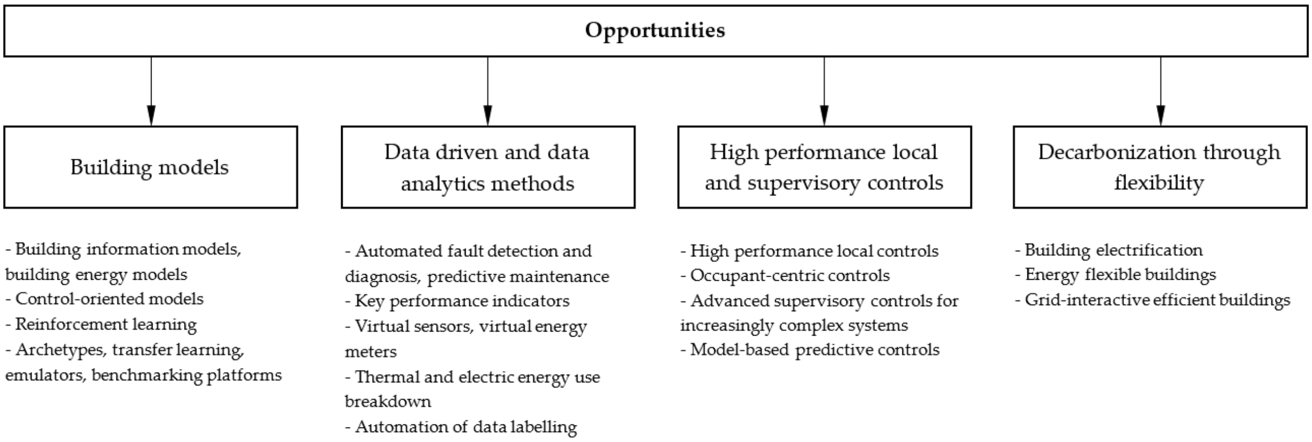


Figure 4. Opportunities related to advanced controls in the built environment.

3.1. Building Models to Support Operational Decision Making

Operational data analysis is critical to better understand how buildings behave and to improve controls. While the analysis of raw data already provides invaluable insights, it also builds the foundations for more advanced approaches where modelling plays a key role. Building models can respond to various control needs and the type of model depends on the application. For instance, models could be tailored for performance tracking, testing of hypothetical scenarios, forecasting of building performance for optimization purposes, and generation of measured and unmeasured synthetic data.

3.1.1. Building Information Modelling and Building Energy Modelling

Various types of building models have been developed in the past and could be useful for control applications. *Building information modelling* (BIM) provides an integrated approach to the management of information for built assets over their lifecycles and aims to facilitate collaboration between disciplines such as architecture, engineering, construction, operations, and maintenance [75]. BIM generally builds upon a rigorously detailed 3D model of the building and gathers relevant information from the design to the operation phase. *Building energy modelling* (BEM), although not necessarily seamlessly integrated into BIM [76], has been extensively used for decades for design purposes and has evolved into dynamic and highly detailed models [77]. Based on physical principles (i.e., mass and energy balance, heat transfer equations), BEM allows for the simulation of the behaviour of a building as a function of numerous variables and parameters such as weather conditions, building geometry and characteristics, internal loads, system schedules and occupancy patterns, generally estimated from design information, educated assumptions, and modeller's experience. These models are mainly developed in a laborious manual process. They have been used for designing new buildings as well as in energy audits, certification programs, and recommissioning studies for existing buildings. In this latter case, numerous (even up to thousands of) parameters can generally be calibrated to make simulation results match monthly energy bills and, in some cases, operational data. Therefore, the calibration of such models is a challenging but essential step to building confidence in model utilization since there have been significant discrepancies between simulated and measured energy use [78]. An important drawback of most BEM tools is that these modelling platforms were mainly developed for design and are not necessarily suitable for controls, making the testing of control strategies even more challenging.

3.1.2. Control-Oriented Models

Control-oriented models (COM), i.e., models accurate enough for decision-making for a specific goal but simple enough to be easily incorporated in further calculations [63], have then appeared and can be distinguished among others by their simpler structure (more suitable for optimization), an appropriate selection of input variables (including controllable variables and disturbances such as weather and occupancy), and a shorter time-scale (usually minutes to days, rather than one year) [79]. These simplified yet accurate enough models are generally calibrated using sub-hourly operational data, but their structure makes them more easily generalized from one building to another, compared with BEM. These models are applicable for different scales, from a specific zone to the whole building, and target various outputs such as thermal behaviour (e.g., indoor air temperature, thermal comfort), energy usage, and system performance [32]. Control-oriented models are generally divided into three categories [21,32,80]:

- White-box models;
- Black-box models;
- Grey-box models.

Whereas white-box models are physics-based, for which new generation building performance simulation software such as Modelica-based tools are clear examples [72,81], black-box models, such as machine learning models, solely rely on operational data. They aim to find the relationships between a set of inputs and outputs. Grey-box models appear as a compromise between white-box and black-box models since they are based on physical principles but are calibrated with operational data. Table 1 summarizes the differences between white-box, grey-box, and black-box approaches for control-oriented models. However, there is no clear distinction between these categories (white, grey, black) but rather a continuum with different "shades of grey" [80]: a resistance-capacitance (RC) thermal network, whose parameters have been estimated from domain knowledge could be categorized as a white-box model, whereas state-space models having only parameters with physical meaning could be considered as grey-box models [32].

Table 1. Distinction between white-box, grey-box, and black-box approaches.

Modelling Type	White-Box	Grey-Box	Black-Box
Techniques	Physics-based models	Resistance-capacitance thermal networks	Artificial Intelligence, time-series, state-space models
Typical software	EnergyPlus 23.1.0, TRNSYS 18, Modelica * v4.0.0	Modelica * v4.0.0, Matlab R2023a, Python * 3.8.8, R * 4.2.1	Matlab R2023a, Python * 3.8.8, R * 4.2.1
Principles	Based on physical principles generally coupled with design data	Based on physical principles generally coupled with operational data	Solely based on operational data, without any physics insights

Table 1. *Cont.*

Modelling Type	White-Box	Grey-Box	Black-Box
Benefits	+ Based on design information + Detailed physics-based simulation + Suitable for testing detailed scenarios (e.g., equipment, occupation) + Controls at a more granular level	+ Compromise between white-box and black-box models + Requires smaller datasets + Flexible and robust to extrapolation	+ Ease of development + Suitable for AI techniques, entirely based on data + Knowledge of building systems and operation not required
Drawbacks	- Usually calibrated with energy bills, rarely with operational data - Low flexibility, adaptability - Development requires significant efforts	- Model structure determined on a case-by-case basis - Diverse estimations required (parameter, system state, etc.) - Less detailed than white-box models, less accurate than black-box models	- Requires larger datasets - High overfitting likelihood - Less reliable for extrapolation (i.e., operating conditions not seen during model development)
Examples of applications	Hypothetical scenario testing, virtual sensors and meters, FDD, MPC	Virtual sensors and meters, FDD, predictive maintenance, MPC, load disaggregation, load forecasting	FDD, predictive maintenance, MPC, load disaggregation, load forecasting, automated data labelling, measurement and verification

* These programming languages are generally used with compatible packages or libraries for modelling.

3.1.3. Reinforcement Learning

Another control approach has recently emerged, *Reinforcement Learning* (RL), as a substitute for conventional control techniques [24,33,82]. RL is an agent-based AI algorithm where agents are trained based on given environmental conditions to take actions that optimize an objective function. Depending on the performance resulting from a given action, a reward function is used to either penalize or encourage it and aims to help agents improve their decision-making process. These agents generally rely on machine learning algorithms and do not require knowledge of building systems and operation; however, they are time- and data-demanding (years of data are required) [33] and face several practical challenges such as model dimensionality, latency, and result interpretability [82].

3.1.4. Software Tools, Control-Oriented Archetypes and Transfer Learning

Different initiatives have been conducted to exploit modelling capabilities for control purposes. An extensive review of software tools for building modelling, simulation, and control for MPC applications has been conducted by Drgoňa et al. [21] and tackles building energy simulation tools, control-oriented modelling tools, MPC design tools, and solvers. Kazmi et al. [83] have focussed on model requirements as well as popular modelling techniques and software packages for load forecasting. Grey-box models were also identified as a pathway for the systematic application of advanced controls in buildings through the notion of control-oriented archetypes [80]. These archetypes are "*reduced-order models that can provide a generic representation for a common zone or building geometry and mechanical system configuration, and which can thus provide enough information to evaluate the effect of control sequences in the short-term and thus inform decision-making*". This approach is seen as a potential breakthrough in generating versatile control-oriented models to develop general control policies and strategies for typical buildings and to facilitate the dissemination of model-based solutions. On a relatively similar topic, transfer learning [84] has gained in popularity and aims to answer the question: "how can one building benefit from another building's modelling and controls project?" Simply said, transfer learning intends to transfer models trained for highly instrumented buildings to buildings with limited available data. Four main applications were identified: building load prediction, occupancy detection and activity recognition, building dynamics modelling, and energy systems control [84,85].

3.1.5. Large-Scale Comparison of Control Strategies and Models

Furthermore, building models and advanced control strategies have recently elicited great research interest and new models and strategies have been investigated for buildings. However, they have mainly been applied to specific case study buildings and datasets, which makes a fair comparison between them difficult to perform. In this context, the tool BOPTEST (building optimization testing framework) has been developed and aims to enable rapid, repeatable deployment of common building emulators representing different system types [86]. These emulators enable testing and comparing different control strategies in standardized conditions. Similarly, the ASHRAE Great Energy Predictor III competition [87,88] was a machine learning contest for long-term prediction with an application to measurement and verification. This competition allowed for the testing ofthe performance of diverse machine learning techniques on the same datasets, composed of over 20 million points of training data from 2380 energy meters collected for 1448 buildings from 16 sources. Likewise, *CityLearn*, an OpenAI Gym environment, has been developed to provide a benchmark platform that helps facilitate and standardize the evaluation of RL agents [82]. It was the foundation of the CityLearn Challenge, where five teams competed in training the best RL agent targeting the management of a microgrid of nine buildings [89]. On a related topic, the M4 competition [90] has evaluated 61 forecasting methods on 100,000 time-series data from a wide range of domains such as industry, finance, and demographic. The project ADRENALIN is another recent initiative of data-driven smart building competitions [91].

3.1.6. Ties between Modelling Approaches

As shown in Figure 5, the abovementioned modelling techniques could be linked together to improve building controls. Among others, BIM could be used to partially automate the development of BEMs; BIMs could support the management of architectural information and operational data, which will facilitate the development of COMs; and BEMs could work as virtual testbeds to test control strategies developed with COMs. In addition, COMs could also rely on a combination of white-box, grey-box, and black-box models.

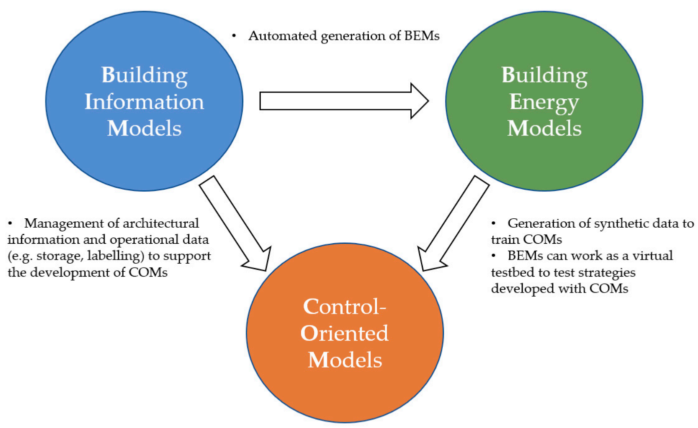


Figure 5. Schematic of some potential links between building information models, building energy models, and control-oriented models.

3.2. Data-Driven and Data Analytics Methods to Improve Building Operation

Operational data represents essential information to investigate in-depth the actual operation and performance of building heating and cooling systems, and it often reveals that systems should be operated differently. However, it is still unclear for practitioners how to leverage operational data to optimize building performance. While FDD commercial products have already shown good promise [10], other methods based on data-driven and data analytics methods could complement these tools to improve building operation and performance.

3.2.1. Fault Detection and Diagnostics, and Predictive Maintenance

FDD commercial tools generally use a rule-based approach to detect operational faults. For instance, current temperature readings and setpoints are compared and an alarm is triggered when the difference becomes too large and exceeds a pre-defined threshold. Moreover, FDD tools usually focus on the first D in the acronym, which is detection. The second D, i.e., the diagnosis, or at least the *correct* diagnosis rather than several potential diagnoses [11], deserves more attention. Research has focussed on automating this process (Automated FDD or AFDD). Models can be developed to supplement the rule-based approach and make the detection more robust [19]. These models, either knowledge-based or data-driven [20], could then help flag performance degradation while providing insights to correctly diagnose faults. Other initiatives, such as automated fault correction, can be found in the literature to reduce the reliance on human intervention while making the diagnosis more proactive [92]. The access to fault datasets for existing buildings during normal operation, rather than faults artificially generated (simulation, experiments), remains a challenge for FDD applications [19,20]. Similarly to FDD, predictive maintenance also plays an important role; unlike preventive measures planned heuristically, predictive maintenance relies on models to predict when a component requires maintenance or replacement [19]. These models, which learn from operational data, identify conditions that may lead to failure events, thus enabling corrective measures that can increase equipment lifetime and save costs. Typical faults requiring maintenance are refrigerant leakage, heat exchanger fouling, pump clogging, damper jam, and coil blockage [27]. FDD and predictive maintenance tools could be incorporated into a broader predictive maintenance strategy, where a BIM model could be used along with operational data to facilitate day-to-day building operation [93].

3.2.2. Key Performance Indicators

Key Performance Indicators (KPI) could help quantify building energy performance, provide more comprehensive operational insights, and track performance degradation over time at the component, system, and whole building level [30,94]. These KPIs have been commonly used at the *whole building* level for performance rating (e.g., energy use intensity, carbon footprint) or at the *component level* for code compliance purposes (e.g., coefficient of performance, heating seasonal performance factor) [94]. KPIs at the *system level* are far less common; they quantify the performance of an entire system providing building services, considering the contributions and impacts of all its components. System-level KPIs can point directly to the system or group of components that should be prioritized in a building. They could thus highlight performance issues, which would remain undetected otherwise (e.g., longer HVAC operation time than required, excessive perimeter heating) [30]. Li et al. [94] developed a comprehensive set of system-level KPIs and calculated them for 16 U.S. DOE commercial prototype buildings using EnergyPlus building models. However, the adoption of these system-level KPIs for existing buildings is still in its early stages [94]; this can be partially explained by the following:

- The lack of sensors and submeters;
- The cost-effectiveness of implementing such KPIs;
- The unknown typical values that can be expected;
- The lack of knowledge of the appropriate KPIs to apply for a given situation.

The development of KPIs becomes even more crucial to assess advanced performance, such as building electric peak load management [28] and energy flexibility [95]. Another benefit of data-driven KPI is the ability to capture the actual system performance. For instance, two theoretically identical systems, such as heat pumps [65] or chillers [96], could show different performance curves in real-life performance; this difference could be further exploited in operation to maximize building performance. KPI could also be used for FDD applications by comparing measurements with the expected performance [20].

3.2.3. Virtual Energy Meters and Load Disaggregation

Another application is the development of *virtual sensors* and *virtual energy meters* to infer unmeasured variables, as discussed in Section 2.2.1. Virtual sensors are mathematical models that predict a variable using measurements available from other installed sensors; similarly, virtual energy meters predict the energy consumption of a building zone or one of its systems [60]. Although more operational data are available, some key variables are still not measured and virtual sensing or metering is a cost-effective solution as a substitution for installing new physical devices, which can be costly and face practical issues [60]. Li et al. [97] reviewed virtual sensing technologies used in buildings. They investigated various virtual sensors, including air and refrigerant mass flow rates, air temperature (outdoor, mixed, supply, return), refrigerant pressure, air humidity ratio, as well as compressor volumetric efficiency, chiller efficiency, valve leakage, and coil capacity.

In addition to the calculation of unmeasured variables, virtual energy meters allow to determine energy flows within a building—for instance, per floor, per air handling unit (AHU) or per variable air volume (VAV) box—and contribute to a better understanding of thermal energy-use breakdown in buildings [98]. Virtual energy meters also unlock many opportunities, such as [60]

- Performance tracking (daily and weekly patterns and schedules, nature of the load, energy distribution, performance degradation),
- Energy-use mapping (aiming at better matching building energy usage with actual occupant's needs),
- Inefficiency detection (by analyzing the load distribution),
- Operation optimization (using gained information for improving building modelling and optimization through advanced controls).

Virtual energy meters are not the only method to break down building energy usage. Load disaggregation methods have emerged as promising techniques to estimate energy end-uses for specific systems or equipment from total electric and thermal energy usage measured by a single meter [30,60]. By means of models, electric and/or thermal load can be disaggregated into different categories such as space heating and cooling, ventilation (fresh air), distribution (AHUs), and/or occupant-controlled (lighting, plug loads), among others [99–101]. Physical submetering of energy usage is still an option to encourage occupants to change their behaviour to save energy [102], although it is relatively costly.

3.2.4. Automated Data Labelling

A key barrier to understanding and analyzing building datasets at a large scale is the lack of standardized variable nomenclature. To reduce the effort required for data interpretation, inference techniques could be used to label data and generate descriptive names without the need for intensive human labour. Diverse automated methods have arisen to infer contextual information from operational data. For instance, Waterworth et al. [103] developed a novel neural language processing method that aims to automatically segment sensor metadata into tokens (i.e., words and sub-words), which is further used for tagging; data from over 182 buildings were used in this study. Chen et al. [104] proposed a method to classify variables according to their type (e.g., indoor air temperature and setpoint, air flow and setpoint, and damper position) only based on numerical values; the approach was applied to zone-level metadata in two office buildings. Mishra et al. [105] presented a unified architecture, which uses time-series data and raw variable names and builds upon rule-based logic and machine learning techniques to apply Haystack tags to variables; this architecture was applied to three commercial retail buildings and one office building. These methods showcase the various possibilities to address the challenge of automating data labelling in buildings. In the future, large language models and other AI techniques may facilitate data management and interpretation.

3.3. High-Performance Local Controls and Advanced Supervisory Controls

3.3.1. High-Performance Control Sequences

Inefficient local controls are a significant barrier to the adoption of advanced controls. The recently released *ASHRAE Guideline 36* [57] inventories various high-performance control sequences to enhance HVAC air-side and water-side system operation. These standardized sequences aim to reduce the time dedicated to developing and implementing local controls and could already help achieve significant energy savings while improving indoor air quality. Zhang et al. [106] simulated new control sequences based on G36 for multi-zone VAV systems under different climates, hours of operation, and internal loads. They obtained energy savings between 2% and 75%, with an average of 31% for a medium-sized office building and found that supply air temperature reset, duct static pressure reset, and zone airflow control contributed the most to these savings. Saloux and Zhang [96] evaluated the impact of a supply air temperature reset strategy based on outdoor air enthalpy for an existing large commercial building; they found that the building cooling load could be decreased by 13%, resulting in a 9% reduction in cooling system electric energy. Nassif et al. [107] built upon G36 to develop new strategies to reset supply air temperature and zone minimum airflow rate setpoints for typical VAV systems; the authors showed a potential of 2–6% fan energy decrease and 8–34% heating load reduction. Lu et al. [108] compared the performance of G36 for supply air temperature and static difference pressure setpoints with intelligent controllers (optimization-based controller and deep reinforcement-learning-based controller) for a simulated medium-sized office building with a multi-zone variable air volume cooling system. G36 sequences demonstrated for this case study similar performance in terms of energy efficiency and thermal comfort compared to the intelligent controllers.

3.3.2. Occupant-Centric Controls

In addition to these energy efficiency measures, the integration of occupant behaviours into building controls has elicited an increasing interest and has led to the development of occupant-centric controls [34,109]. A large range of applications can be found: temperature and humidity setbacks, demand controlled ventilation, temperature setpoint adaptation to occupants, and illuminance adaptation to occupants (preferences, vacancy off) [25,26]. The data required for these controls—such as occupant presence (binary patterns), count, and activity (thermostat use behaviour, comfort feedback)—show high temporal and spatial variability [25]. As a result, gathering occupants' feedback data through web, mobile, and wearable applications has become crucial. In this respect, mobile applications [110] and "smartwatches" [111] capable of retrieving occupant's thermal comfort feedback and platforms to improve workspace allocation based on the occupants' activity [112] provide new data sources. A critical review of field implementations of occupant-centric building controls has been conducted by Park et al. [26]. The impact of the global COVID-19 pandemic has disrupted the way buildings are occupied. Adapting building controls to individual preferences while maintaining an energy-efficient building operation may emerge as a key feature of the next generation of controls.

3.3.3. Supervisory Controls for Complex Integrated Energy Systems

With the advent of increasingly more efficient technologies, building heating and cooling systems have become more and more complex and the optimal design and control of these systems are far from being straightforward [113]. Advanced control strategies are thus required to exploit their full potential and advanced supervisory controls are promising solutions. Unlike local controls that ensure the operation of individual devices, advanced supervisory controls target system-level operations and aim to fulfill the role of the master controller discussed in Section 2.3.1. While individual components could be competing to maximize their own performance, advanced supervisory controls use a bird's-eye-view to optimize the system's performance as a whole, which incorporates heating and cooling systems, on-site energy generation from renewable sources, and energy storage devices. Although most buildings still use conventional methods, new technologies have emerged and could play a more significant role in commercial and institutional buildings in the near future:

- Heating and cooling systems generally consist of rooftop units, electric and natural gas boilers, electrical baseboards, connection to district heating, mechanical chillers, etc. Technologies such as evaporative cooling [114], air-source and ground-source heat pumps [95], and high-temperature heat pumps (currently mainly for industrial applications [115]) will become increasingly present.
- On-site energy generation systems from renewable sources may include photovoltaic and photovoltaic/thermal systems [116], wind turbines [117], solar collectors [118], as well as organic Rankine cycles [114,119] (mainly used for waste-heat recovery at the moment [120]).
- Regarding energy storage devices, batteries represent the main electrical storage device option; electric vehicles and associated charging stations could provide some opportunities for electric load management as well [121]. Radiant floors [95], water tanks, and geothermal fields are common options for thermal energy storage; electrically heated thermal storage [95] is becoming more and more popular. Phase change materials, although mainly used in the residential sector [122], could emerge as a potential solution for commercial buildings [123]. For cold storage, ice banks have shown encouraging promise [124,125].

These numerous systems add complexity to building controls on top of the already existing variety in HVAC system configurations (e.g., air handling units, fan coil units, terminal units, variable refrigerant flow), which make each building practically unique. Figure 6 shows some of the possible heating, cooling, and distribution systems, along with electricity generation and energy storage devices that could be found in commercial and institutional buildings. This is where building modelling (see Section 3.1) could be a game changer in testing different control strategies and determining the optimal operation of integrated systems. It could be achieved through model-based controls (MBC) [96], targeting the use of models to estimate building performance and optimize the operation, as well as model predictive control (see Section 3.3.4), also based on models but taking advantage of available forecasts to anticipate changes and adjust accordingly. Reinforcement learning [33] is another type of control technique based on models to address supervisory controls. Furthermore, such controls could be applied at different levels, from the equipment level (e.g., zone supplied by dedicated heat pump and radiant floor [95]) to the central plant (e.g., chilled water plant [96]) and the building level [64]. The use of control-oriented archetypes [80] and building emulators to test control strategies [86] could facilitate the development of general models and control solutions to eventually foster supervisory controls deployment.

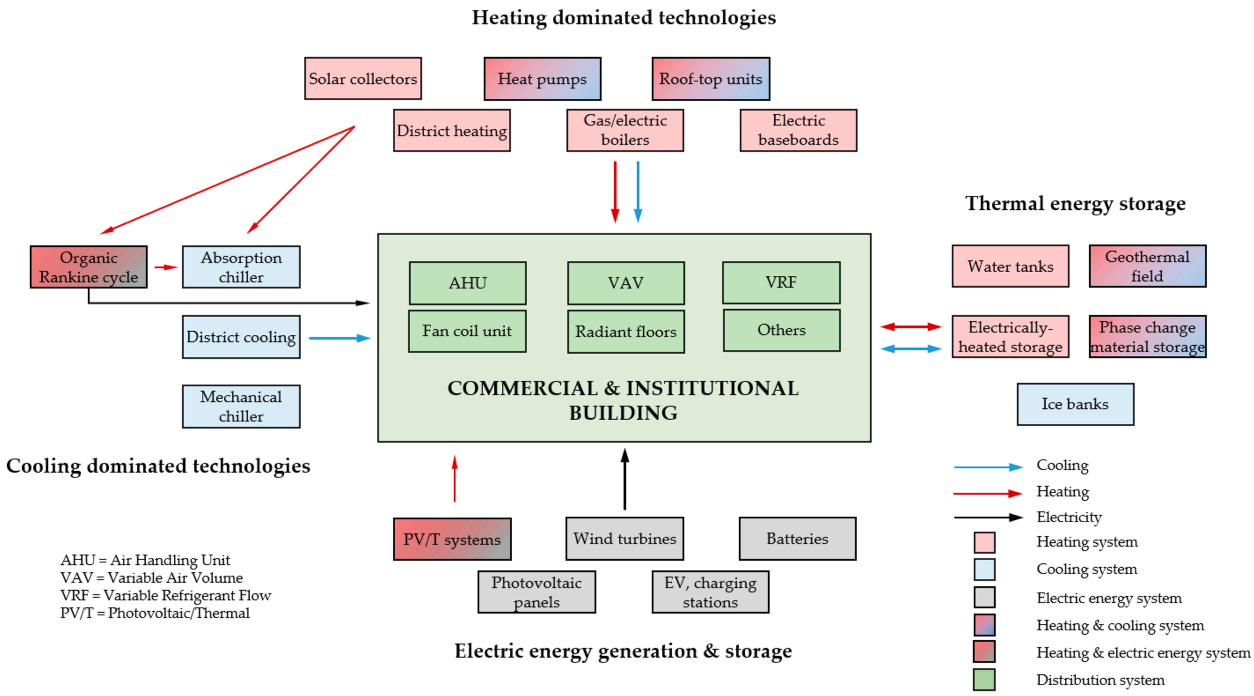


Figure 6. Schematic of some technologies which could be used for heating, cooling, and electricity generation in commercial and institutional buildings.

3.3.4. Model Predictive Control

In addition to inefficient local controls, buildings are currently mainly operated in a reactive manner and simply respond after a change occurs. Advanced controls such as model-based predictive control can enable buildings to be proactive by anticipating changes and adjusting accordingly to satisfy a given objective. Such strategies could build on various forecasts such as weather conditions, occupancy patterns, dynamic energy costs, and grid carbon intensity to satisfy objectives such as the reduction in energy use, energy costs, peak demand, GHG emissions, or the improvement of indoor environment quality and thermal comfort. For example, by anticipating solar gains in a zone, the heating power could be reduced beforehand to avoid overheating and thermal discomfort. Similarly, a building could be preheated at night in anticipation of a cold morning to avoid excessive electric peak load in the morning. This topic of model-based predictive control has raised much interest for the past decades and has shown promising results. Several review papers can be found in the literature on this topic:

- Drgoňa et al. [57] performed a thorough review of MPC for the built environment, from the structure and formulation to the deployment and performance assessment.
- MPC for HVAC systems has been reviewed by Afram and Janabi-Sharifi [22], Serale et al. [126], and more recently by Yao and Shekhar [23] and Taheri et al. [127].
- MPC for energy storage has been investigated by Thieblemont et al. [128] and Yu et al. [129].
- Péan et al. [130] have focused on MPC for heat pumps.
- Mirakhorli and Dong [131] and Park et al. [26] concentrated on occupancy behaviour-based MPC and occupant-centric building controls.

Control-oriented modelling has been acknowledged as the cornerstone of MPC, and its development takes a significant share of the effort required for developing and implementing MPC strategies: up to 70% of project costs are attributable to model creation and calibration [132]. Whereas white-box models are favoured for simulation-based MPC studies, black-box and grey-box models are used more in actual experiments [32]. A recent publication suggested shifting from model-centric MPC to data-centric MPC to address the heterogeneity among buildings and the need for model customization for each building [133]. MPC faces other practical challenges that hold up massive deployment, such as data availability and processing, MPC scheme, qualification of control engineers, and risk mitigation of MPC implementations [9,134]. Nonetheless, a few initiatives can be reported. Vallianos et al. [135] investigated the aggregated effect on the grid of model predictive control strategies applied to 7500 houses in Canada using the Ecobee dataset [50], whereas Deng et al. [55] evaluated the potential of data-driven predictive controls for 78 commercial buildings using the data available in the RTEM database [54].

3.4. Decarbonization and the Need for Energy Flexibility

3.4.1. From Energy Efficiency to Decarbonization

Current control strategies have mainly focused on minimizing building energy use, energy costs (especially under a real-time electricity pricing rate), and electric peak load [72]. In the context of climate change and GHG emission reduction targets, these objectives have been slightly reoriented towards building decarbonization, which requires a new paradigm shift. The electrification of buildings is seen as an essential means to achieve it, especially in countries where electricity is already generated from low-carbon sources (e.g., hydroelectricity) or where renewable energy shows a possibly reasonable penetration rate. To reduce the current and future burden on the electric grid's infrastructure, buildings should not be optimized in a siloed manner anymore but must be part of the Smart Grid and must become good grid citizens.

3.4.2. Energy Flexible Buildings

The concept of energy flexibility [136] is becoming critical, and buildings can play a significant role. IEA EBC Annex 67 Energy Flexible Buildings defined the energy flexibility of a building as the "*ability to manage its demand and generation according to local climate conditions, user needs and energy network requirements*" [137]. Built on this concept, the U.S. DOE introduced the notion of *grid-interactive efficient buildings* (GEB), which are "*energy efficient buildings with smart technologies characterized by the active use of distributed energy resources to optimize energy use for grid services, occupant needs and preferences, climate mitigation, and cost reductions in a continuous and integrated way*" [138]. Simply said, buildings should be able to manipulate their electric load to improve grid reliability: they should reduce their energy usage during the grid's peak hours (downward flexibility), whereas they should help store the grid's energy surplus when available (upward flexibility, e.g., from solar plants during sunny days, from wind farms during windy days). Buildings can provide different grid services [138]:

- Efficiency (consistent load reduction; for instance, more efficient HVAC systems);
- Load shedding (temporary load reduction such as lighting dimming);
- Load shifting (load shifted to off-peak periods such as building preheating);
- Power modulation (e.g., grid frequency and control system voltage);
- Power generation (such as on-site photovoltaic).

To provide these services, multicarrier systems combining different energy vectors (e.g., electricity, natural gas, oil, biomass) are particularly of interest and show high flexibility potential with their ability to switch from one energy source to another (e.g., dual fuel boiler, electrically driven heat pump with natural gas fired boiler) [136]. Many indicators have been proposed in the past to quantify building energy flexibility. Li et al. [29] have reviewed 48 of them that are related to peak power and energy load shedding, peak power and energy rebound, valley filling, load shifting, energy storage capability, demand response costs savings, and environmental impact, among others.

3.4.3. Role of Advanced Controls to Enhance Flexibility

In the meantime, at the building level, advanced controls are essential to ensure the continued operation of critical building services, and to improve building resilience and climate-readiness. Therefore, advanced control strategies offer considerable opportunities to unlock the flexibility potential of buildings [139] and might take advantage of dynamic price signals and the electric grid's real-time carbon intensity to minimize building GHG emissions while maximizing profitability and satisfying building objectives such as thermal comfort and GHG emission reduction targets. MPC is an appropriate measure to achieve higher flexibility in buildings. As a complementary measure, policy incentives should tackle the carbon intensity of buildings and the electric grid as a whole, for example, by applying dynamic (e.g., hourly) GHG emission factors. The flexibility potential for building communities harnessed by aggregators and for district energy systems could even be more attractive with additional thermal energy storage capabilities and aggregated benefits [136].

4. Hierarchy of Advanced Controls

Sections 2 and 3 dealt with pressing challenges and promising opportunities in building operation where various topics were tackled and targeted a large number of applications at different scales. This section aims to organize these topics together and develop a hierarchy in advanced controls opportunities and requirements. Inspired by the energy management hierarchy of needs developed by Nexus Labs for smart building platforms [140], Figure 7 shows a hierarchy of advanced controls opportunities and requirements for buildings.

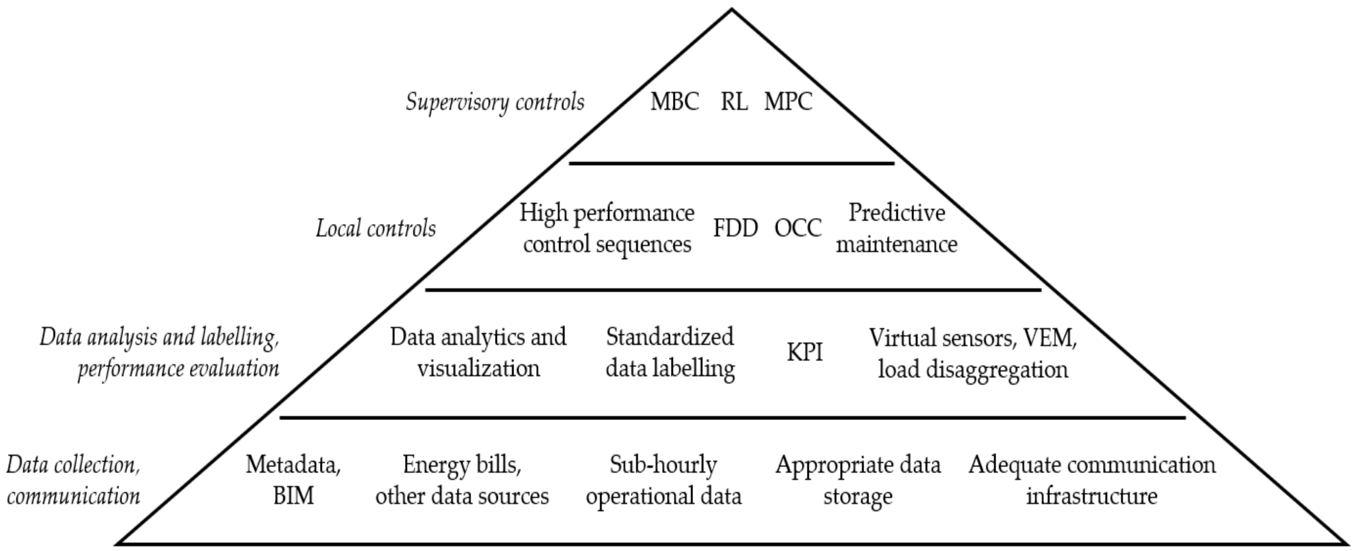


Figure 7. Hierarchy in advanced controls opportunities and requirements.

The lower level represents enablers for advanced controls in buildings, which are mainly related to available data and communication considerations. It includes the access to general building information such as metadata, BIM (Section 3.1.1), energy bills, and other data sources; the availability and storage of sub-hourly operational data (Section 2.2); and an adequate communication infrastructure (Section 2.3). The second level corresponds to data analysis and performance evaluation. It refers to data analytics and visualization tools, but it also covers proper data labelling (Section 3.2.4) as well as virtual sensors, energy meters, and load disaggregation to monitor key variables that are not measured (Section 3.2.3), and finally, key performance indicators to track building and system performance (Section 3.2.2). The third level tackles the improvement of local controls and includes various applications, from fault detection and diagnostics and predictive maintenance (Section 3.2.1) to high performance control sequences (Section 3.3.1) and occupant-centric controls (Section 3.3.2). Finally, the higher level builds upon local controls improvements and optimizes the operation of complex integrated energy systems to maximize the performance of the building heating and cooling systems as a whole. It could rely on MBC (Section 3.3.3) and RL (Section 3.1.3) but also MPC (Section 3.3.4) by leveraging available forecasts such as weather, occupancy, energy prices, and the grid's carbon intensity (Section 3.3). Flexibility (Section 3.4) could be incorporated in the objective function to transition from building energy efficiency to building decarbonization.

Such a categorization is certainly no easy task and relies on the authors' experience and personal assessment. The goal of Figure 7 is to emphasize the main trends, although there might be no clear distinctions between categories and levels (Figure 1), similarly to the different "shades of grey" in control-oriented models (Section 3.1.2). For instance, RL and MPC could be used for local controls (e.g., setpoint tracking) but they show higher potential for supervisory controls to optimally operate complex integrated building systems (setpoint optimization, central plant control). MBC could be used to improve local controls as well, but we see it more in facilitating the development and adoption of supervisory control solutions (Section 3.3.3). FDD, OCC, and predictive maintenance algorithms might be already based on models and could be seen as MBC to some extend; similarly, some MPC strategies can be occupant-centric [62]. KPI are shown in Figure 7 in the second level for performance evaluation, but it could be used as well for FDD (Section 3.2.2). Data labelling, virtual sensors, and virtual energy meters could be seen as enablers (lower level); nonetheless, advanced controls could still be developed even if variable nomenclature is not standardized, or virtual energy meters are not yet available.

5. Conclusions

Commercial and institutional buildings are currently not operated at their full potential, resulting in suboptimal performance that could be addressed by more appropriate control strategies. Although the potential of advanced controls such as MPC is proven, massive deployment in existing buildings is still not a common practice. This article has focussed on pressing challenges and promising opportunities in building controls. It aims to provide researchers, practitioners, and newcomers in the field with a state-of-the-art overview of the situation. The numerous, significant current challenges are grouped into six categories:

1. Existing local control flaws that need to be addressed in order of priority. Old control infrastructure is a crucial hurdle for adopting increasingly more complex mechanical systems.
2. With the advent of the digital era, operational data have become increasingly available for buildings and are of paramount importance for advanced controls; however, data are not necessarily available or appropriately stored in every building, key variables are not necessarily well measured (or measured at all), variable labelling is often confusing, and data could simply not be shared.
3. Current building automation systems have been designed in a siloed manner and communication with the control system is no easy task, nor can it support advanced calculations; cybersecurity and local security considerations add another layer of complexity.
4. There is, in general, a lack of guidelines tailored for control applications that address standardized high-performance building control sequences, the evaluation of control-oriented model performance, and the assessment of energy and economic savings.
5. Economic feasibility and expected savings of advanced controls still need to be widely acknowledged; successful case studies are rare, and more policy incentives are required to encourage adoption.
6. Engagement between industry and the research community still needs to be improved; however, practitioners may face a knowledge gap and require appropriate training to keep up with a fast-evolving, technology-driven world.

On the other hand, four main streams of opportunities were identified:

1. Building modelling is the cornerstone of advanced control strategies; BIM and BEM, control-oriented models, and reinforcement learning can serve several objectives, whereas different initiatives, such as archetypes, emulators, benchmarking platforms, and transfer learning, aim to scale and generalize existing models and control strategies.
2. Data-driven and data analytics methods allow us to provide invaluable insights into building operations and facilitate the development of advanced controls; this includes the development of KPIs, virtual sensors and energy meters, load disaggregation methods, and automated data labelling.

3. Attempts at high-performance local controls and advanced supervisory controls have shown encouraging prospects; work should be continued towards this direction. MPC promises to make buildings more proactive by anticipating changes rather than being reactive and simply responding after a change occurs.
4. In the context of climate change, decarbonization of buildings is vital. It requires a new paradigm shift: advanced control strategies could help make buildings become energy flexible, more resilient, and good citizens of the smart grid.

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Abbreviations

AFDD	Automatic fault detection and diagnosis
AI	Artificial intelligence
ASO	Automated system optimization
BAS	Building automation system
BEMS	Building energy modelling
BEMS	Building energy management system
BIM	Building information modelling
COM	Control-oriented modelling
EIS	Energy information system
EMIS	Energy management and information system
FDD	Fault detection and diagnosis
HVAC	Heating, ventilation, and air conditioning
IPMVP	International performance measurement and verification protocol
G36	ASHRAE Guideline 36
GEB	Grid-interactive efficient buildings
GHG	Greenhouse gases
KPI	Key performance indicator
MBC	Model-based control
MPC	Model predictive control
OCC	Occupant-centric control
RL	Reinforcement learning
RTEM	Real time energy management
VAV	Variable air volume

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