

Journal Pre-proof

Adaptive-predictive control strategy for HVAC systems in smart buildings
– A review

Maryam Gholamzadehmir, Claudio Del Pero, Simone Buffa,
Roberto Fedrizzi, Niccolo' Aste



PII: S2210-6707(20)30700-9
DOI: <https://doi.org/10.1016/j.scs.2020.102480>
Reference: SCS 102480

To appear in: *Sustainable Cities and Society*

Received Date: 30 November 2019
Revised Date: 28 March 2020
Accepted Date: 10 September 2020

Please cite this article as: Gholamzadehmir M, Del Pero C, Buffa S, Fedrizzi R, Aste N, Adaptive-predictive control strategy for HVAC systems in smart buildings – A review, *Sustainable Cities and Society* (2020), doi: <https://doi.org/10.1016/j.scs.2020.102480>

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2020 Published by Elsevier.

Adaptive-predictive control strategy for HVAC systems in smart buildings - A review

Maryam Gholamzadehmir ^{a,b*}, Claudio Del Pero ^a, Simone Buffa ^b, Roberto Fedrizzi ^b, Niccolo' Aste ^a

^aArchitecture, Built environment and Construction Engineering A.B.C., Politecnico di Milano, Via Bonardi 9, 20133 Milano, Italy

^bEurac Research, Institute for Renewable Energy, Viale Druso1, 39100 Bolzano, Italy

*Correspondence: Maryam.Gholamzadehmir@eurac.edu, Maryam.gholamzadehmir@polimi.it, Via Bonardi 9, 20133 Milano, Italy

Highlights

- Comprehensive review of advanced control strategies and their impact on buildings and technical systems with respect to energy/cost saving.
- Identifying features, applications and functions of building automation and control system (BACS) in buildings and HVAC systems.
- Assessment of the practical implementations and configurations of adaptive-predictive control strategies (APCS) and challenges associated with these strategies.
- Demonstrating research gaps in advanced control strategies (ACS) for buildings and HVAC systems.

Abstract: High share of energy consumption in buildings and subsequent increase in greenhouse gas emissions along with stricter legislations have motivated researchers to look for sustainable solutions in order to reduce energy consumption by using alternative renewable energy resources and improving the efficiency in this sector. Today, the smart building and socially resilient city concepts have been introduced where building automation technologies are implemented to manage and control the energy generation/consumption/storage. Building automation and control systems can be roughly classified into traditional and advanced control strategies. Traditional strategies are not a viable choice for more sophisticated features required in smart buildings. The main focus of this paper is to review advanced control strategies and their impact on buildings and technical systems with respect to energy/cost saving. These strategies should be predictive/responsive/adaptive against weather, user, grid and thermal mass. In this context, special attention is paid to model predictive control and adaptive control strategies. Although model predictive control is the most common type used in buildings, it is not well suited for systems consisting of uncertainties and unpredictable data. Thus, adaptive predictive control strategies are being developed to address these shortcomings. Despite great progress in this field, the quantified results of these strategies reported in literature showed a high level of inconsistency. This is due to the application of different control modes, various boundary conditions, hypotheses, fields of application, and type of energy consumption in different studies. Thus, this review assesses the implementations and configurations of advanced control solutions and highlights research gaps in this field that need further investigations

Keywords: Building automation; Model predictive control; Weather predictive; Grid interaction.

| Nomenclature | | | |
|---------------------|---|--------------|--|
| AC | Air condition | ICT | Information and communication technology |
| ACS | Advanced control strategies | IOT | Internet of things |
| AHU | Air handling unit | MPC | Model predictive controls |
| ANN | Artificial neural networks | nZEB | Nearly zero energy building |
| APCS | Adaptive-predictive control strategies | PID | Proportional, integral, and derivative (control) |
| BACS | Building automation and control system | PV | Photovoltaic |
| BEMS | Building energy management system | RESs | Renewable energy sources |
| CCU | Central control unit | RL | Reinforcement learning |
| CPU | Central processing unit | SB | Smart buildings |
| DHW | Domestic hot water | TCS | Traditional control strategies |
| EU | European Union | TES | Thermal energy storage |
| FL | Fuzzy logic | TOU | Time of use |
| GHG | Greenhouse gas (GHG) | VAV | Variable air volume |
| HVAC | Heating, ventilation and air conditioning | WSANs | Wireless sensor and actuator networks |

1 Introduction

Energy demand in the residential and commercial buildings sector in the European Union (EU) accounts for approximately 40% of total energy consumption (European Commission, 2019a). The outcome of this high share of energy consumption has been a significant increase in greenhouse gas (GHG) emissions from 19% in 2010 to 39% (Eurostat, 2018). Today, there are public concerns about rising energy demands and its adverse impacts on the environment and climate change. Therefore, stricter laws have been put in place in the EU to reduce energy consumption and to promote the application of energy from sustainable resources. In line with EU legislation, the nearly zero energy building (nZEB) and low/zero carbon concepts have been introduced as the basic components of sustainable and socially resilient smart cities and society. nZEB has a very high energy performance with the nearly zero or minimum amount of energy consumption which is mainly supplied from Renewable Energy Sources (RESs) either on-site or nearby (D'Agostino et al., 2016; Kolokotsa, et al, 2011). This concept is designed to accomplish low energy demand buildings by the onsite implementation of RESs from programmable sources (e.g. biomass), and/or non-programmable sources (e.g. solar and wind energies). Matching the energy demand with the power supply from non-programmable RESs is more sophisticated (Butera, F et al., 2018). In this context, smart buildings (SB) were introduced to provide higher flexibility and sustainability, by managing and controlling the energy generation/consumption/storage in the building (European Commission, 2019b). It has been reported that the final energy consumption can be cut down significantly in an SB by using building automation technologies (Dar et al., 2014; Subbaram Naidu & Rieger, 2011a). Thus, the utilization of automated technologies is mandatory in the development of the SB. Due to lack of universal and standardized terms and definitions, a number of various definitions have been reported in the literature for automated technologies, among which the so-called building energy management system (BEMS) or building automation and control system (BACS) are the most common (De Wilde, 2018). Despite different names, the main goal of such systems would be always to save more energy/cost and lower the adverse environmental impacts of buildings. It is worth mentioning that the BACS/BEMS is a combination of hardware and software that controls a buildings' technical systems i.e. lighting/shading, domestic hot water (DHW) and heating, ventilation and air conditioning (HVAC) (Aste et al., 2017). In fact, several recent studies showed that about half of utilized energy in buildings is consumed for the HVAC system (Shi et al., 2017; Mařík et al., 2011; Lee et al., 2015). This emphasizes the importance of the utilization of BACS/BEMS to cover HVAC as an important piece of the whole technical system in each building. In this paper, we will mainly focus on the control strategies, thus only on the software part of a building control system, which will be always named BACS.

By far, different control strategies including traditional control strategies (TCS) to advanced control strategies (ACS) have been used in BACS (Mirinejad et al., 2008). The uncertainty associated with the internal and external environmental factors such as energy loads caused by the users, weather conditions and dynamic energy price limit the application of TCS and impose the need for more advanced solutions. However, in literature, there is a large inconsistency in quantified results and implemented control hypothesis of ACS as well as utilized control components/variables. In spite of a large number of studies in this field, it is not yet clear which type of ACS is the most promising and energy/cost efficient one and what the quantified impacts of ACS are. Additionally, the impact of ACS in different boundary conditions is still unclear. These major gaps make it difficult to define an infrastructure for the optimal configuration of ACS for a building and its technical components. These gaps have not been discussed and addressed in

the literature with sufficient level of detail. Thus, this paper aims to summarize and classify these research gaps through reviewing quantified results of available papers in order to shed a light on the ambiguities and inconsistencies present in this field. This will help to pursue a solution for addressing open challenges. Therefore, the main objective of this paper is to provide an overview of the evolution of control strategies and logics applied in buildings and recent advances in this field. In this context, the main elements of control strategies are reviewed, and advantages/drawbacks are discussed. The paper addresses the most relevant ACS including the best configuration and practical implementation in buildings. More in detail, a literature review revealed that Model Predictive Control (MPC) has been widely implemented and showed some promising features as powerful ACS (Serale et al., 2018). However, its performance needs to be improved by adding more features. A suitable solution is the integration of MPC with adaptive control strategies (Yang et al., 2019; Tesfay et al., 2018). Thus, in this paper, more attention will be paid on Adaptive-Predictive Control Strategies (APCS) as one of the most promising advanced control strategies in buildings. The advanced practical implementation of APCS for SB and HVAC systems is thoroughly investigated and control functions and potential achievable benefits are summarized; obtained results can be used as guidelines for future application of APCS in a more consistent way. The paper is organized as follows: Section 2 provides an overview of control strategies in buildings covering both TCS and ACS; publications with ACS were reviewed in detail (e.g. comparing location, building sector, HVAC system components, type of control strategies, quantified result) to identify potential research gaps and open points in this context. Section 3 aims to define the best configuration of APCS for building and HVAC control, highlighting the practical implementation of this configuration and achievable benefits. In conclusion, section 4 summarizes the pros, cons and open points providing some concluding remarks.

2 Review on Building Automation and Control System (BACS)

A BACS is defined as a computer-based and automated system that analyses the specific necessities of a building by controlling the associated mechanical and electrical plants/equipment installed in the building, thereby can contribute to energy saving without compromising the thermal/visual comfort of users (Aghemo et al., 2014). The primary aim of a BACS is to preserve the thermal/visual comfort of occupants in line with an energy efficient and cost effective building operation (Aste et al., 2017; Hazyuk et al., 2014). It integrates algorithms which substitute user's needs in controlling the technical systems, based on different objectives, such as:

- *thermal/visual comfort*, which is the human body's perception of comfort and well-being as related to environmental temperature and air quality (Hazyuk et al., 2014; Li, Zhang, & Zha, 2019).
- *energy saving*, by applying techniques which ensure the minimum amount of energy without compromising thermal/visual comfort (Manjarres et al., 2017; Dikel et al., 2018; Huang et al., 2015).
- *cost saving*, which deals with increase in energy efficiency, optimized energy consumption, and management of RESs as alternative energy supply in power generation for SB to ensure the minimum operational cost (or maximum income in case of energy-active buildings)(Shan et al., 2016; D'Etorre et al., 2019; J. Ma et al., 2012).
- *optimal interaction with the external environment*: the external environment could be the district or the national grid.

Figure 1 summarizes features and application of BACS and classification of control strategies, as discussed hereafter.

Main control parameters: in any buildings' BACS, there are some parameters that need to be controlled in order to lead the system toward the control objectives. Based on the objectives, these controllable parameters may vary. For thermal comfort, parameters like indoor air temperature, indoor relative humidity and air change rate are the most common; for environmental air quality, it is possible to list CO₂ level and Volatile Organic Compounds (VOCs); for energy and cost saving, temperature and state of charge of storage, load factor of energy generator and heat loss time-lag can be controlled. By far, many research works are dedicated to controlling the technical systems and particularly the HVAC systems (Afram & Janabi-Sharifi, 2014; Behrooz et al., 2018; Royapoor et al., 2018).

Controllable components: they could be categorized into four main parts: energy generation, distribution, emission and storage systems and they can be applied both to HVAC and DHW systems.

Technological elements: a BACS is based on several technological elements and some of them are described in the following:

- *sensors* are the equipment that measures physical quantities and then converts them into digital signals. They are used to monitor environmental data, like temperature, humidity, lighting, CO₂, occupancy, etc. in various parts of the building. It should be noted that the location of sensors is critical in order to gain optimal data. In literature there are some general information about this issue but not fully clear (Rockett & Hathway, 2017);
- the *central processing unit (CPU)* elaborates information from sensors and carries out instructions according to control logics and strategies.
- the *actuators* are used to actuate the control strategy elaborated by the CPU, to directly control the technical equipment of the building including the HVAC appliances (Aste et al., 2017);
- the *information and communication technologies (ICT)* provide the communication infrastructure among sensors, CPU and actuators allowing the interaction with the users, the grid and the external environment (e.g. weather forecast service) by means of wired or wireless technologies.

Classification of control strategies: by far, many different control strategies have been developed for controlling a building and its technical systems. This complicates the selection of the most proper control strategy in each specific application. However, as already introduced, these strategies can be classified into two major groups: traditional control strategies (TCS) and advanced control strategies (ACS). The first one can be in turn classified in *sequencing control* (called also *rule-based control* because it defines the orders/conditions that switch equipment online or moving them offline) and *process control* (adjusts the control variables to achieve well-defined process objectives against disturbances by measuring the state and/or disturbance variables) (Wang & Ma, 2008). As well, different classifications for ACS can be identified according to literature (Afram & Janabi-Sharifi, 2014; Behrooz et al., 2018):

- *soft-computing control strategies*, which include reinforcement learning (RL), deep learning based on artificial neural network (ANN), fuzzy logic (FL) controls and agent-based controls. Soft computing usually can deal with imprecision, uncertainty and noisy input producing approximate/statistical responses. Thereby, they are able to give solutions to more sophisticated problems (Sakunthala & Mandadi, 2018).

- *hard-computing control strategies*, which comprises auto-tuning PID control, gain-scheduling control, self-tuning control, supervisory/optimal control, model predictive control (MPC) and robust control. The common element among all types of hard-computing strategies is the use of a mathematical/analytical model. Such strategies usually require real/precise input data to provide an accurate response quickly. Imprecision and variability are unwanted properties in these strategies (Sakunthala & Mandadi, 2018).
- *hybrid control strategies*, which is a combination of soft and hard control strategies. In the following subsections, a review on TCS and ACS highlighting their main components, features and pros and cons is reported.

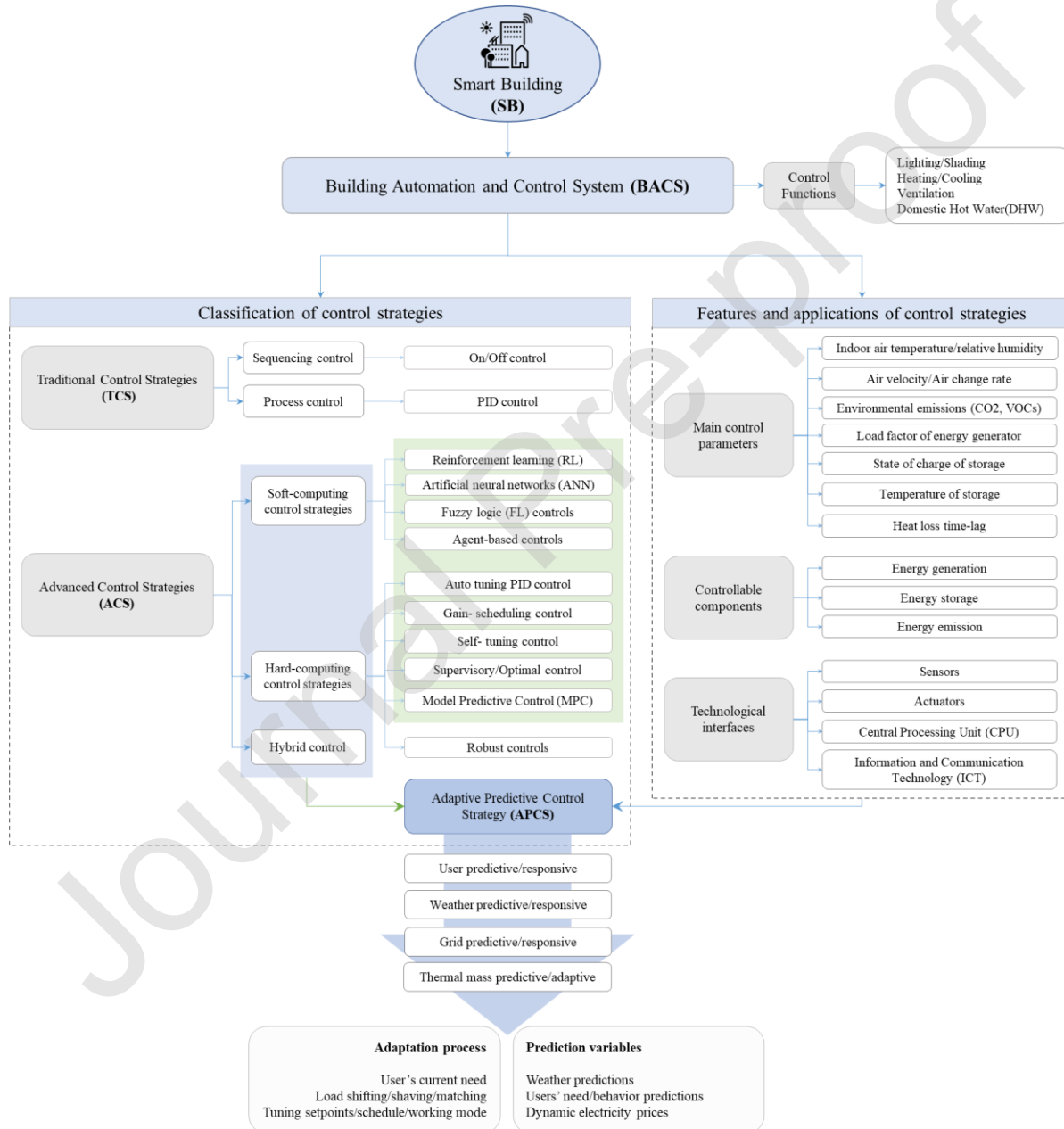


Figure 1. Features, applications and functions of BACS in buildings and HVAC systems.

The green box in Figure 1 highlights adaptive control strategies. A control strategy is adaptive if employs mechanisms (e.g., self-tuning, re-learning) to cope with unforeseeable deviations with respect to the design conditions. To deal with this, adaptive controllers usually include system identification tools that periodically use monitoring data to calibrate the controller parameters or the system model. In contrast with adaptive control strategies, robust controls handle uncertainties by assuming bounds at design time without being able to deal with unpredictable variables observed during the control process. Finally, APCS are a more advanced type of adaptive control. They can combine soft and hard computing control strategies in order to adapt to uncertainties and to define optimal trajectories of the control inputs by exploiting predictive logics.

2.1 Traditional control strategies (TCS)

As presented in Figure 1, TCS comprises two main subcategories: sequencing control and process control (Behrooz et al., 2018). The main logic used in the sequencing control is on/off control whereas the main logic used in process control is proportional, integral, and derivative (PID) control. These types of strategies are typically used to control HVAC components based on the signal of basic sensors such as thermostats, pressure switches or humidistats.

One of the major drawbacks of TCS is the lack of interaction with the external environment (i.e. user/grid/district/city) which precludes the application of high-efficiency control. The main pros and cons of TCS are summarized in Table 1.

Hence, the trend of control systems is toward ACS which have the potential to address the constraints of TCS (Perera et al., 2014). In the following section, the features of the ACS application in the building sector are reviewed.

2.2 Advanced control strategies (ACS)

ACS represent a key step towards improving the energy/cost efficiency in buildings and HVAC systems and aimed to reach all the defined control objectives of BACS (Section 2). ACS are capable to deal with the uncertainty of internal loads caused by the users, or external factors such as weather conditions and dynamic electricity prices (Aswani et al., 2012). In ACS the measured data on energy consumption and user behaviour are collected and used as feedbacks and even inputs to the system to make it more adaptable with the occupant needs (Van de Bree et al., 2014). In the following, the results of analysed publications in the field of ACS have been investigated and reviewed. Although the ACS in the building sector is usually applied to the tertiary sector, there are also successful studies on other buildings typologies i.e. residential buildings (Carrascal-Lekunberri et al., 2017). As represented in, the majority of the works on the ACS address tertiary buildings including offices or educational buildings, which account for 47% followed by residential (34%) and commercial (19%) buildings. Tertiary buildings usually have a pre-defined occupancy schedule which decreases uncertainty factors for the control system. This leads to better and easier control performance eventually. This can clarify the reason why more attention was paid to the tertiary sector in literature.

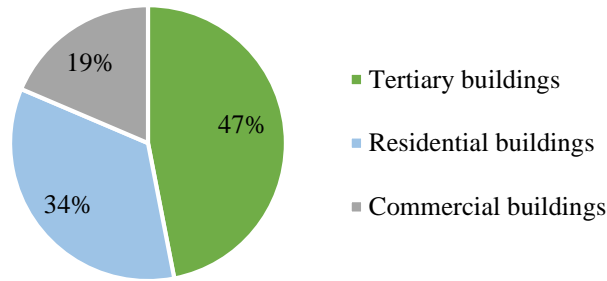


Figure 2. Proportion of building typologies considered for applications of ACS in the literature retrieved from SCOPUS.

Figure 3 represents the field of applications of ACS in buildings technical systems in the literature. As shown in this figure, the majority of ACS applications (almost 50%) are in air handling units (AHU), variable air volume (VAV) and air conditioning (AC) which are the components of HVAC system. In addition, within storage systems, ACS were applied to thermal energy storage (TES) systems in the literature (Yu et al., 2015; Thieblemont et al., 2017) whereas it has been applied to electrical storage systems in recent years. Moreover, some researches concentrated on artificial lighting, appliances and shading systems produced promising results with respect to energy/cost

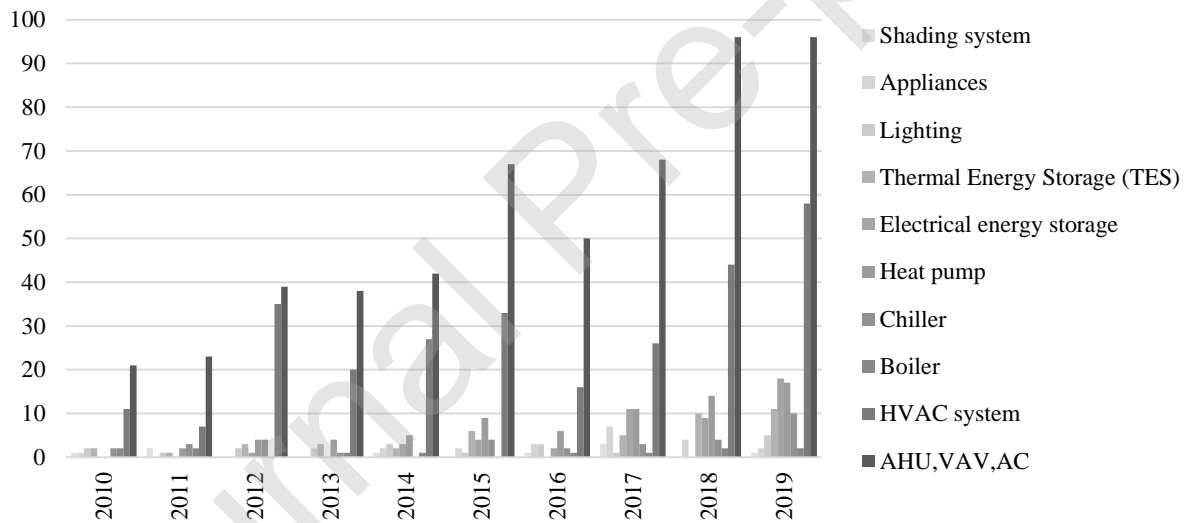


Figure 3. Number of publications for field of applications of ACS in the literature retrieved from SCOPUS.

saving. Accordingly, the air handling process could represent more than 60% of the total energy consumed by the HVAC system in the tertiary sector (Kusiak et al.,s 2011).

Figure 4 represents different approaches of ACS applied in buildings and HVAC systems by researchers over the last decade (from 2010 to 2019). As shown in this figure, among those ACS, model predictive control strategies were the most widely used accounting for almost 50% of publications and only a few studies were conducted on the APCS. Therefore, the next sub-sections carefully assess MPC, highlighting its advantages and limitations followed by a comprehensive review of the APCS.

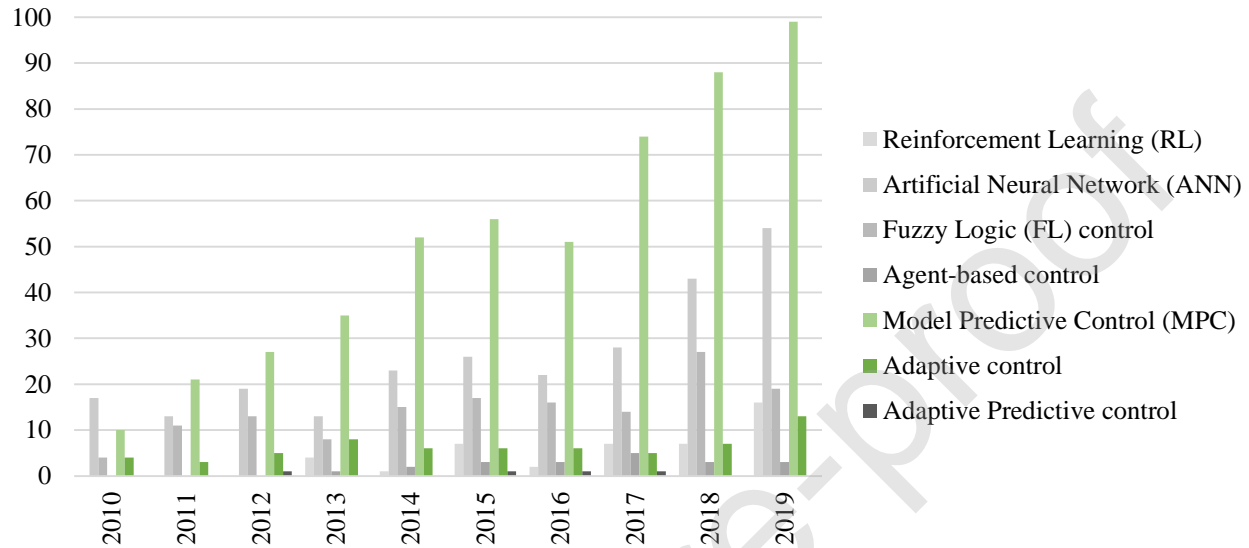


Figure 4. Number of publications for different approaches of ACS in the literature retrieved from SCOPUS.

2.2.1 Model predictive control (MPC) strategies

Recently, the application of MPC strategies in BACS has received significant attention from the research community (Serale et al., 2018). By incorporation of renewable energy generation, new solutions for technical systems (e.g. heat pumps) and energy storage systems, an ACS with forecasting feature, known as MPC, is required to reach high energy and comfort performance levels. A common application of MPC in the building sector comprises the prediction of the dynamic behavior of systems in the future and adjustment of response by the controller accordingly leading to energy and cost saving while satisfying thermal comfort (Serale et al., 2018; Hazyuk et al., 2014). It is worth mentioning that several researchers demonstrated that MPC has a significant potential for saving energy and cost in buildings with high thermal capacity (Le Dréau & Heiselberg, 2016; Dounis & Caraiscos, 2009). In fact, the building's thermal mass could be seen as a storage medium. the storage potential in the thermal mass was evaluated in residential buildings with MPC to achieve a better understanding of the dynamic behavior of buildings (Le Dréau & Heiselberg, 2016). Similarly, optimal exploitation of passive and active thermal energy storage capacities to cover the cooling demand of an office building has been investigated by (Henze et al., 2004) by means of sequential time block optimization over a horizon of 24 hours. MPC is an appropriate choice for handling the slow moving process with time delays and therefore it is well-suited for HVAC systems (Behrooz et al., 2018). In fact, MPC strategies consider the information related to the technical system as well as the predicted future external and internal environmental data of building such as weather forecast, building load, occupancy and energy

prices to obtain an optimal value of control function at defined control time-step for the system (Luzi et al., 2019; D’Ettorre et al., 2019). Although most of the applications of predictive control are for tertiary buildings, (Fielsch et al., 2017), it is claimed to be beneficial for simple and small systems like those of residential buildings, as well. Nevertheless, the expectation of the reduction of energy consumption and cost when compared to tertiary buildings is lower (Fielsch et al., 2017). However, large distributed MPC implementation in residential buildings can unlock large demand flexibility providing important benefits to power grid operators as assessed by (Corbin & Henze, 2017). In order to enable optimization of the building energy performance, the MPC needs to monitor and control the changes in building response over time. Thus, it is possible to start with a simple initial model to begin the control operations which will be replaced by an improved model in the near-future through re-estimated input data (Rockett & Hathway, 2017). The predictive model relies on the quality of the input data, therefore the role of sensors reliability and the place they are installed are of high importance. Additionally, the implementation of MPC offers possibilities for the control to be based on occupant comfort rather than the zone temperature (Rockett & Hathway, 2017). Another great feature of MPC is that it can also deal with the complexity of building thermal behavior and the occurrence of disturbances and uncertainties that adversely affect the performance of the system. In fact, the MPC method is widely used in process control applications (Behrooz et al., 2018) and has been successfully applied to occupied buildings (Kolokotsa et al., 2009).

Therefore, (Afram & Janabi-Sharifi, 2014) performed a comparison of MPC with other control approaches for improving energy flexibility by means of heat pump systems. It has been concluded that MPC affords higher energy performances and shows more steady performance with varying input parameters compared to other control strategies. MPC strategy has the possibility of verifying energy conservation and it can be applied for thermal energy storage systems management. This enables peak load shifting/shaving/matching strategies. Nonetheless, weather prediction, the accuracy of the model and disturbance effects all can affect the mismatch between predicted and real energy consumptions and thus the MPC performance. (Y. Ma et al., 2010) evaluated MPC for optimal thermal energy storage in building cooling systems. Their experiments showed that MPC can achieve reduction in the electricity cost of thermal energy generation and storage system along with 11.9% improvement of the thermal energy efficiency. Moreover, (Frauke Oldewurtel et al., 2012) claimed that stochastic MPC is a promising approach for building climate control. However, its performance in real applications could be expected to vary with the quality of the model and the available input data.

MPC causes better performance of the system through control of numerous variables, consistent response improvement, prediction of future control schedules, future disturbance estimation, improved transient response, handle slow moving processes with time delays (Perera et al., 2014). The different functions of MPC in buildings can be summarized as follows.

- *Weather predictive/responsive*, which is the buildings’ capability to predict/respond to external climate conditions and to identify the best operating profile accordingly. The weather forecast model could be offline or online. MPC is able to respond to climate conditions and implement passive and active measures to maximize energy efficiency and minimize the energy taken/fed into the grid. By application of weather forecast, (Barzin et al., 2016) saved energy by 30% and cost by 41% in an experimental study on test huts. Moreover, the advancements of IoT and cloud-based strategies made it easier to get information from weather data (Biyik et al., 2015). (Kelman, Ma, & Borrelli, 2011)

proposed an MPC approach in a typical commercial building for two common HVAC configurations to minimize energy consumption while satisfying occupant comfort by using weather prediction data.

- *User predictive/responsive*, which is the capability of the building to enable prediction and real-time interaction of users with the implemented technologies. Learning from occupant's behaviour and impact of occupants on internal gains/loads estimation are among the main features of MPC which can have a great influence on enhancing energy performance (Serale et al., 2018). A key function of a BACS is that it can switch off the technical systems in an unoccupied period and guarantee the thermal comfort of users in the occupied period (Javed et al., 2017; Yang et al., 2016). As claimed in (Ponds et al., 2018), the user interacts with the MPC to automatically create optimal load operation schedules, specifying different priorities and their comfort settings. (Ahmadi-Karvigh et al., 2019) proposed a framework with the aim of improving the energy efficiency of appliances and lighting systems in office and apartment testbed buildings considering adaptation with occupants' activities, preferences and dynamics. Daily energy consumption saving of 5% to 45% by adaptive automation of control system has resulted. Moreover, (Frauke Oldewurtel et al., 2013) investigated MPC with the potential of using occupancy information on the technical system of Swiss office buildings to evaluate a more energy efficient building climate control
- *Grid predictive/responsive*, which is the buildings' action/reaction to signals/information coming/predicting from the grid, usually with the aim to maximize the energy/cost efficiency at district/city scale. When the dynamic electricity price is applied to the system, MPC defines a load scheduling for the system to regulate correlation between time of consumption and peak load shifting/shaving/matching with the grid thereby energy/cost saving (Aste et al., 2017; Liu & Heiselberg, 2019). MPC under different conditions decides to switch working modes between direct use of the on-site energy generation, energy storage system, the benefit to store energy (both thermal and electrical) or feeding in/buying from the grid. In this respect, ACS defines the optimal cost/energy decision making.
- *Thermal mass predictability/adaptability*; the building's thermal mass can significantly affect the building energy load due to its considerable capacity and resistance (Dong et al., 2018). Cooling/heating stored in the building's thermal mass can affect the control function. MPC is able to use the potential of the building thermal mass to modulate the energy generation, consumption and storage of the system (Schmelas et al., 2016). It can take advantage of building thermal mass to shift energy demands to off-peak hours through adaption mechanisms.

The most common prediction data used in MPC were identified based on data published in the literature, and are represented in Figure 5. As shown in this figure, weather forecast and building load prediction are the most common prediction data used in field of ACS.

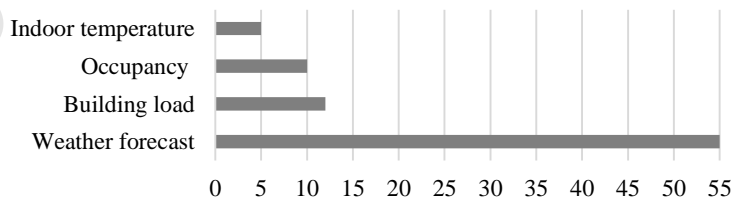


Figure 5. Prediction data of ACS in the literature retrieved from SCOPUS.

One of the main issues in predictive control strategies is the evaluation of an accurate prediction horizon based on the system's characteristics. To date, most of the research on predictive control evaluated the prediction horizon of one day ahead (D'Etorre et al., 2019; Liu & Heiselberg, 2019). (Luzi et al., 2019) investigated the tuning of control variables including prediction and control horizon. The result showed that one-day ahead prediction was the best setup to enhance energy saving and thermal control. The literature review revealed that one-day ahead is the most common setup for prediction and horizon control. However, tuning of prediction and control horizon might be impacted by the building boundary conditions i.e. climatic context, building characteristics. Therefore, more investigations are required to assess the correlation between prediction and control horizon and various building boundary conditions for optimal energy and cost saving outcomes.

Additionally, it is reported that MPC would not provide precise and fast outputs while facing a high level of uncertainties in the system (Maasoumy et al., 2014). Uncertainty of the MPC is due to the imperfect predictions of internal and external heat gains of the building as well as uncertain load prediction (Xu et al., 2019; Liu & Heiselberg, 2019).

Different boundary conditions occur in experimental implementations regarding external and internal disturbances acting on the system, such as weather conditions, occupancy activities, types of equipment and etc., which may significantly affect the result of the control strategy (Afram & Janabi-Sharifi, 2014; Behrooz et al., 2018). Therefore, it is not simple to evaluate the performance of controllers with these inherent disturbances in the building (Oldewurtel et al., 2010; Gyalistras & Division, 2010). Moreover, MPC requires a proper model of the system. Under these conditions, it is difficult to obtain a perfect prediction of the loads in future times (Luzi et al., 2019; Maasoumy et al., 2012). Based on the carried-out review, the main pros and cons of MPC are summarized in Table 2.

Based on the analysis of data provided in the literature and discussed further in this work, the performance of predictive control systems might be improved by adding more features. Taking into account the control objectives of building and HVAC system, the MPC with described limitations could not be adequate for highly efficient control of buildings' energy systems. As a solution, many studies suggest integrating adaptive control strategies and MPC in order to address the limitations of MPC (Buonomano et al., 2015; Mizumoto & Fujimoto, 2012; Maasoumy et al., 2014) which are discussed in more detail in the following section.

2.2.2 Adaptive control strategies

The main characteristics of an adaptive control strategy are its complexity, nonlinearity and time varying essence (Subbaram Naidu & Rieger, 2011b). In fact, this strategy is compatible with nonlinear models and slow time delay systems and uncertainty (Nounou & Nounou, 2011).

The term "adaptive" allows certain flexibility in controlling unpredictable and unknown behaviour of the building (Buonomano et al., 2015), whereas the "adaptive approach" provides the desired set points, schedules or working modes (Short, 2012). (Candanedo & Athienitis, 2011) mentioned the advantages of adaptive control strategies which reveal an increase in the performance of the HVAC system with higher stability level comparing to other strategies. Based on this control strategy, parameters can vary fast in response to changes that allow achieving better performance of the system.

(Perera et al., 2014) considered the adaptive control strategies as a specific kind of nonlinear control methods, that are compatible with processes or systems where the dynamics change

through regular operating conditions because of stochastic disturbances. (Tang & Chen, 2019) implemented adaptive control strategies for artificial lighting of a tertiary building and the total consumption compared to the traditional lighting system was able to save 40% of energy consumption. (Behrooz et al., 2018) noted advantages of adaptive control strategy which reveals an increment in performance of the HVAC system with higher stability level comparing to other strategies. Based on this control strategy, parameters can vary quickly in response to changes. These control strategies respond rapidly to changes that cause a better performance of the system. Adaptive strategies have been also implemented for the HVAC system where different hypotheses, system configurations and thus, different energy savings have been reported. Table 3 summarizes the main pros and cons of adaptive control strategies (Aswani et al., 2012; Yan et al., 2008).

Despite many reports on the merit of ACS for energy/cost savings, a deep review of the reported results published in the literature shows that they are highly inconsistent and widely variable. These great variabilities could be attributed to the applied hypotheses comprising different boundary conditions, control system configurations, technical system application and the practical implementation of the control system.

2.2.3 Research gap of ACS in literature

Energy saving potentials have been reviewed more in detail in various types of energy consumption (i.e. thermal, electrical, primary and total consumption and peak power demand) based on seasonal mode (i.e. heating, mid-season and cooling mode). Reports with no specified type of energy consumption were also included in this review in the category of total energy consumption. Different publications reported the energy saving potential in theoretical and/or experimental assessments using different boundary conditions, configurations, variable fields of applications. Quantified impacts of ACS for energy saving in residential and tertiary sectors are represented in Figure 6 and discussed as in the following.

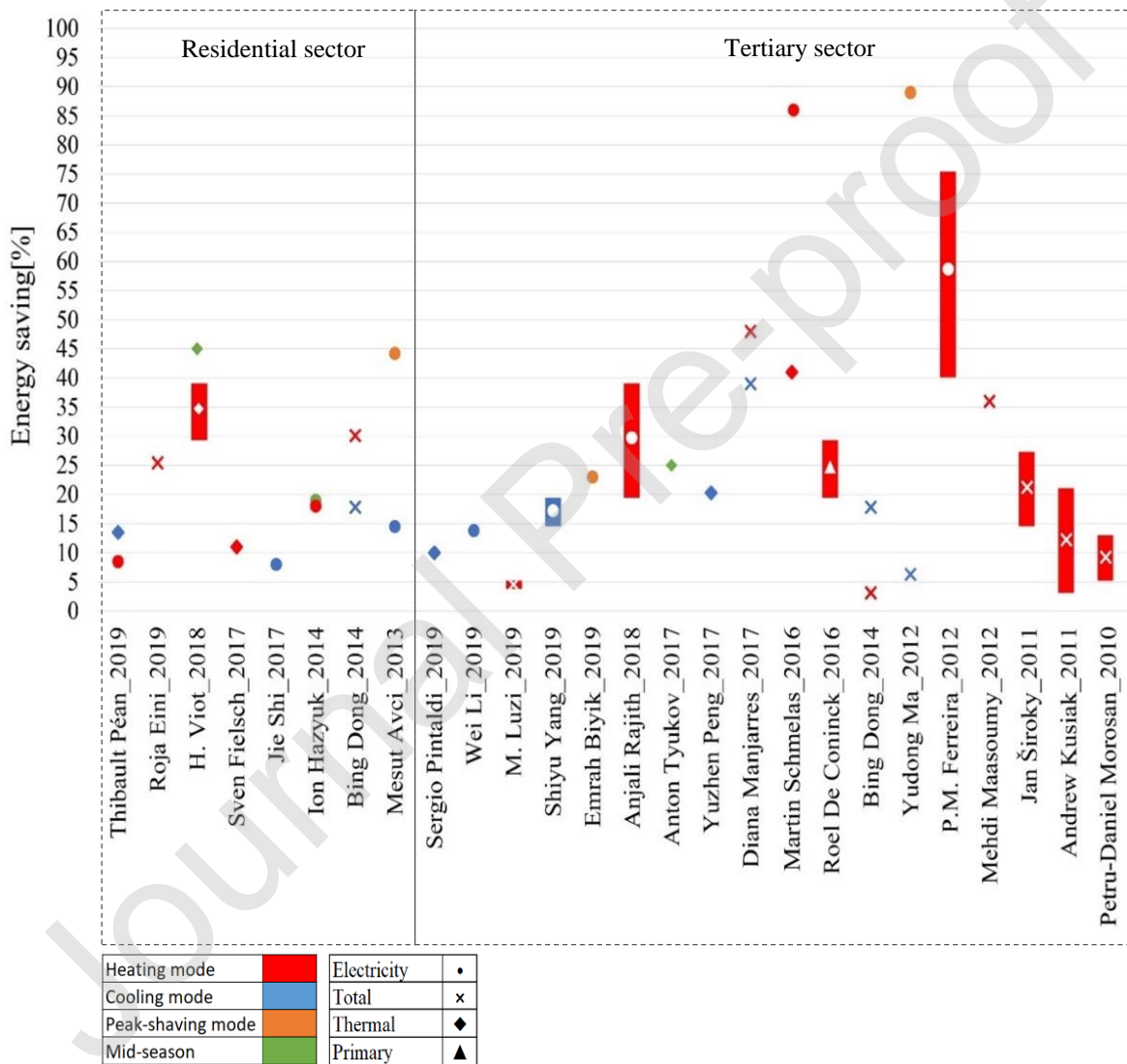


Figure 6. Energy saving potential by applications of ACS in the analyzed literature.

Residential sector: the highest thermal energy saving potential reported is 45% in mid-season and 30% to 40% in heating mode, respectively by comparison of MPC with two conventional control strategies in an experimental assessment (Viot et al., 2018). For electrical energy consumption, (Avci et al., 2013) attained 44.2% of reduction in energy consumption by load control of HVAC with MPC in peak-shaving mode and 14.5% in cooling mode. Additionally (Hazyuk et al., 2014) reported 18.2% of electrical energy saving by comparison of MPC vs. scheduled PID in heating mode and 18.3% in a typical mid-season.

Tertiary sector: (Schmelas et al., 2016) reached savings of over 41% for thermal energy consumption by implementing an ACS through experimental assessment in heating mode. In addition, they claimed that electrical pump energy could be reduced by more than 86% in heating mode, which was one of the highest electrical energy saving reported among the reviewed publications. Besides, (Ma et al., 2012) saved 69% of electrical energy in peak-shaving mode by using a predictive control with thermal storage system in an experimental assessment. Other noticeable energy saving results were reported by (Ferreira et al., 2012) in the range of 41% to 77% for electrical energy consumption in heating mode which was accomplished by neural networks based predictive control. Likewise, (Rajith, 2018) reported savings in electrical energy consumption in heating mode from 20% to 40% using MPC on top of an IoT.

In addition to energy, cost saving results were also reviewed and summarized in Figure 7. (Afram et al., 2017) reported a wide range of cost savings between 6% and 73% depending on the season for MPC compared to the fixed set-point control. They also provided a summary of energy/cost savings from different publications that used Artificial neural network (ANN) based MPC approaches and reported energy savings in the range of -4.5% to 18% (a negative energy savings value means that the higher energy was consumed compared to baseline and vice versa).

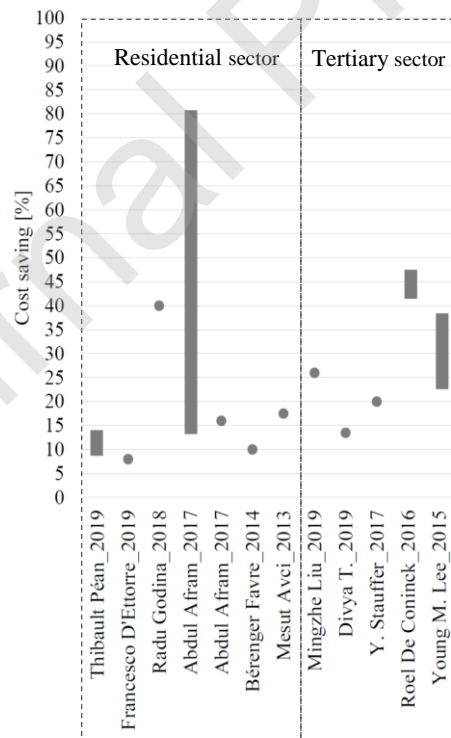


Figure 7. Energy saving potential by applications of ACS in the analyzed literature.

In summary, it should be noted that it's difficult to make a comparative conclusion and meaningful relationship between results from various publications mainly because of different hypotheses and assumptions in each publication. Thus, the real impact of ACS in buildings is not clear. However, it is useful to discuss maximum and minimum achievable energy savings through ACS in different boundary conditions. Range of energy and cost savings reported in Figure 6 and Figure 7 widely vary depending on locations, type of building sectors, field of applications and type of control systems, etc. Part of variations are also related to the selection of ACS, different configuration of ACS as well as it's practical implementation in buildings and technical systems.

In the field of ACS, there are many works on predictive control and adaptive control strategies, but only a few works focused on the combination of predictive control and adaptive control strategies, a fairly new concept referred to as "adaptive-predictive control strategy (APCS)" for thermal control of buildings that can cover all the control objectives of an SB (Schmelas et al., 2016; Yang et al., 2019). As a result, it is not still clear what is the best way to configure this APCS and how to put it in practice in order to achieve ACS objectives in the most efficient way. Thus, in the following section, APCS is thoroughly reviewed, highlighting its functions, advantages and the best configuration of practical implementation for energy/cost savings in the building sector.

2.2.4 ACS overview in research and development

Several EU researches projects have been funded to study ACS application in building systems. One of the first, funded under the FP4-NNE-JOULE C EU program (FP4-NNE-JOULE C EU program, 1998), dealt with the application of fuzzy logic controllers to improve HVAC management and comfort conditions in buildings; in another one, funded under the FP7-PEOPLE program, stochastic MPC has been studied by ETH Zürich (CORDIS, 2014; Frauke Oldewurtel et al., 2015) for energy efficient management of building systems and power grids. The Horizon 2020 (H2020) program funded also the completed projects SMARTCIM (SMARTCIM, 2015) and BuildingControls (BuildingControls, 2016) that aimed at developing IoT solutions for making hydronic components smarter and enabling demand response participation of buildings by applying MPC, respectively.

Recently-closed and ongoing EU research projects include H2020 HIT2GAP (HIT2GAP, 2016) where a server-based BEM system has been developed to reduce the gap between design and real energy consumption of buildings. In the H2020 BuildHeat project (H2020 BuildHeat project, 2019) an ANN-based MPC algorithm has been developed to maximize RESs exploitation in a multi-family house by means of an air-source HP and a solar thermal field connected with decentralized thermal energy storage systems. A preliminary implementation of a smart control algorithm has been done in the H2020 project HYBUILD (H2020 project HYBUILD, 2013) to achieve intelligent management of hybrid storage systems to cover the building's thermal loads by means of a reinforcement learning algorithm. The application of adaptive-predictive control strategies is foreseen in the H2020 project HEART to enable the application of optimal control strategies in multifamily houses taking into account possible deviations of building's behaviour as well as end-user habits. Moreover, there is also a trend in the application of ACS to unlock building flexibility and interaction at the district level with respect to electricity and thermal grids. Demand response strategies and building flexibility have been studied in the H2020 projects Sim4Blocks (H2020 projects Sim4Blocks, 2017) and Rennovates (REnnovates, 2011) whereas in the H2020 EnergyMatching project it is foreseen the implementation of ACS to maximize at district level the

use of locally harvested heat and electricity by means of façade and rooftop PV/T and HP systems. Similarly, the implementation of sector coupling throughout ACS will be demonstrated in several district heating and cooling networks within the recently founded H2020 project REWARDHeat (H2020 project REWARDHeat, 2020).

In the last decades, ACS have been successfully implemented and developed for application in the process industry. Nowadays several companies are trying to enter into the building sector market. For instance, Honeywell (Stluka, Mařík, & Endel, 2014; Wen, 2018) developed an adaptive cloud-based MPC to be integrated into BACS. Siemens Building Technologies Division and IBM started a partnership (Construction Week Online, 2016; Siemens, 2011) to develop a cloud-based BEM system exploiting data analytics and IoT technologies. DesigoTM (Siemens, 2011) is the BACS from Siemens with adaptive features. Recently, ABB (ABB, 2020) acquired Cylon Controls Ltd (Cylon Controls Ltd, 2019) and have invested in Enervalis (Enervalis, 2018) strengthening its offer for smart building applications throughout adaptive ACS solutions.

Few emerging SMEs started their business dealing with the application of ACS in buildings and energy systems. Some examples are the implementation of real-time cloud-based MPC by (QCoefficient Inc, 2017) that exploits the building thermal mass and HVAC system part-load characteristics of buildings achieving peak shaving as well as HVAC energy costs reduction especially in those countries where the electricity market allows large commercial buildings to participate in real-time energy markets and demand response programs. Deployment examples include the Willis (formerly Sears) Tower in Chicago with over 400,000 m² of floor area and the Morgan Stanley headquarters in New York City. Another small company is (ODYS Srl, 2019) that developed a proprietary Quadratic Programming solver for the implementation of real-time MPC in embedded systems targeting different application domains.

3 Adaptive-predictive control strategies (APCS)

APCS method is able to adapt to a controlled system with time-dependent variables through online variation of its control gains (Buonomano et al., 2015). APCS focuses on dynamic and adaptive processes instead of static and predefined parameters for control. This means that the system itself can outline appropriate setpoints, schedules and working modes for the technical system of the building within a certain time based on the monitoring data analysis through the adaptation process (Short, 2012).

(Yang et al., 2019) implemented an adaptive robust MPC in an experimental assessment. An adaptive building model along with online building operation data to estimate uncertain parameters such as internal loads and a robust optimization formulation have been utilized. (Schmelas et al., 2016) reported that the major complication in control of thermo-active building systems (TABS) is due to the large thermal inertia, and the fact that their parameterization is time-consuming. It is concluded that conventional TABS-control strategies could not efficiently maintain the required thermal comfort in buildings particularly when the internal heat sources are disrupted suddenly. Then, the implementation of adaptive predictive control for TABS achieved successful results. (Tefay et al., 2018) claimed that for a strongly nonlinear plant with a dramatically time varying characteristics an adaptive MPC mechanism can cope with the degradation issue. Using this strategy, the parameters were tuned continuously through recursive estimation and update approaches, which makes the MPC less sensitive to prediction errors and helps to achieve the optimal superheat response (Tefay et al., 2018). (Lauro et al., 2014) evaluated adaptive MPC strategy for indoor temperature regulation of and multizone office building using electrical heaters. They reported that the distributed MPC strategy with dynamic weighting coefficients of the cost

function was the best one in terms of energy saving and comfort. Furthermore, (Tanaskovic et al., 2017) reported the adaptive MPC strategy was an efficient solution for handling uncertainties in building climate control while satisfying comfort even during the adaptation phase.

3.1 Functions of APCS

APCS is well suited for target systems including nonlinear processes, time delays, high dynamic and it can deal with uncertainty parameters (Yang et al., 2019; Behrooz et al., 2018). The promising functionalities of APCS include weather prediction, user response, grid/district/city interaction, thermal mass additivity (Schmelas et al., 2016). Load shifting/shaving, state of charge of storage and feeding the grid are the main sub-functions of grid interaction whereas heat loss time-lag is the sub-function of thermal mass (the ability of a building material to absorb, store and release heat energy). Well-insulated buildings have long time-lags which make it difficult to maintain thermal comfort in case of when the occupants' internal gain increases significantly in the building (Le Dréau & Heiselberg, 2016; Carrascal et al., 2016). In this situation, APCS is a suitable solution which is able to quickly respond by manipulating the corresponding variables. Generally, APCS makes the decision to set optimal manipulated variables i.e. setpoints, schedules and working modes based on collected internal/external environmental data and boundary conditions. Then APCS implements control law that takes the current sensor values and prediction data; then attempts to set up the actuators to fulfil the users' preferences and energy efficiency as well as cost optimal target.

Manipulated variables may vary at a supervisory level or at the component level (Thieblemont et al., 2017). One of the main functions of the APCS is to provide optimal control settings at the supervisory level to achieve the desired tracking objectives. Based on the prediction data, measured parameter and current output of the system APCS choose the optimal setpoints, operational schedules (Luzi et al., 2019) and working modes (Sala-Cardoso et al., 2018) for the technical system.

Given the advanced features and functions of APCS which have been discussed in detail, it is a powerful control strategy for building especially when the control system aims to face uncertainty factors and disturbances. However, wide ranges of energy/cost saving by using APCS have been reported in the literature suggesting that more comprehensive studies are required to have a robust understanding of the quantified achievements of APCS.

3.2 Advanced practical implementation of APCS

Research has identified some challenges and constraints regarding the implementation of control strategies in real cases. One of the main challenges that affect the performance of control strategies is the lack of optimal external and internal data collecting/analysis/connecting from the building and its' technical system. Besides, technology trend shows a tendency toward wireless and unconventional technologies such as the internet of things (IoT) and cloud computing. Currently, researches about IoT in SB are mainly focused on ICT and sensor technologies. (Coates et al., 2017; Cao et al., 2010; Guestrin, 2005) used wireless sensor and actuator networks (WSANs) in their work and considered joint problems of control and ICT in WSANs for building control. (Wei & Li, 2011) assessed wireless sensor network which can connect sensors (lighting sensor and HVAC sensors) to accomplish the acquisition of consumption information data in SB. They send the environmental information data of building, HVAC and any subsystems through sensors to the central control unit (CCU) of the building. (Minoli et al., 2017) studied the technical challenges and opportunities provided by IoT integration in commercial buildings. Further, they claimed that the IoT offers strong capabilities in energy savings, demand response and cost savings for users,

moving them up the automation continuum to an SB status (Png et al., 2019). Overall, IoT technology is therefore focused on monitoring, communication, data collection and analysis rather than automation and control. The benefits of using this information to inform and improve decision making related to building automation are numerous and powerful.

Furthermore, IoT with cloud computing improves data collection and their integrated application can be a source of virtual connection for external and internal environmental data of the building. This brings more accuracy to the control system inputs. Thus, the cloud approach is capable of reducing costs through energy efficiency, while suitably meets the comfort standards of inhabitants (Vafamehr & Khodayar, 2018).

Recent work on cloud computing inspired researchers on more unconventional implementation of ACS in the building sector. In literature, it is concluded that a cloud-based strategy can be assessed for executing the complex control algorithms of the HVAC system that can embed more function (Javed et al., 2017).

Therefore, APCS can be implemented in two ways: local and cloud-based. In the latter case, the functions of the APCS can be centralized in a cloud platform. It is worth to mention that the best configuration is the simultaneous implementation of local at the building level and cloud-based for centralizing different information and transmission of data to the local controller. In case of a disconnection of the cloud platform, the local controller can still manage the buildings properly with some APCS features. However, cloud technology can add extra benefits and functions to the system. Figure 8 shows the supervisory level of control logic for APCS in SB. The cloud platform gathers all the data including external environmental data; current external weather condition and grids' TOU price, disturbances prediction parameters and data collected from local CCU including internal environmental data; parameters related to indoor thermal comfort, HVAC operation, user's behaviour and user's current need. Based on these collected data and pre-defined working schemes of the technical system, cloud-based APCS regulates the operation of the HVAC components and defines the priority for working schemes, manipulating setpoints and schedules for the system.

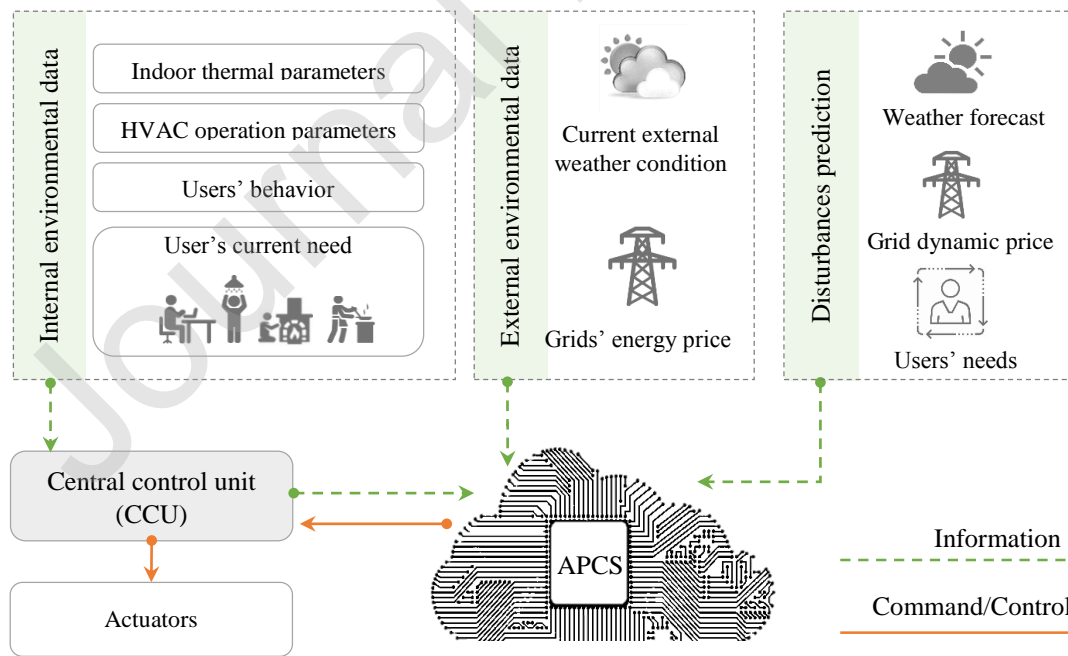


Figure 8. Application of APCS as a supervisory control system through a cloud platform.

Potential features that cloud-based APCS may bring to the SB are listed as following:

- *centralized data collecting*, to monitor/collect the information relating to the operation and performance of technologies (Javed et al., 2017).
- *advanced/rapid data processing and analysing*, by using the cloud to process the large external/internal data of the building, like controllable parameters to optimize energy metrics (Javed et al., 2017).
- *optimized solution*, since the platform could provide optimal solution/response and send command/control signal to the CCU
- *scalability*, using big data which makes the building/technical system capable of connecting/controlling at the district/city scale.
- *data accessibility*, building information will be available/controllable on any connected devices at anytime

3.3 The achievable benefits of APCS

The potential benefits that adaptive and predictive control schemes can bring to building environment control applications such as HVAC have been well documented in recent years (Maasoumy et al., 2014; Schmelas et al., 2016; Yang et al., 2019; Beiyan, 2018). The applicability of prediction provides an online solution of optimal control problems, where tracking the prediction error is possible (M. Xu & Li, 2007). Terms of adaptive bring great control flexibility for unpredicted and unknown behavior of the external/internal environment of SB (Buonomano et al., 2015). It has been reported that APCS has a significant potential for saving energy and cost by exploiting the building's thermal mass (Luzi et al., 2019; Hazyuk et al., 2014). Overall, APCS achieves better performance; more desirable thermal comfort and a significant reduction of energy/cost compared with other strategies (Yang et al., 2019). Table 4 summarizes the main pros and cons of APCS.

4 Conclusion

In many countries, the highest share of energy consumption occurs in buildings which provide a great opportunity for saving energy as well. BACS including TCS and ACS have been proposed to reduce energy consumption and improve energy efficiency in residential/tertiary buildings. Despite many advantages of ACS reported in literature, there are main open challenges with respect to their application in buildings/HVAC systems as listed below:

- *Inconsistent quantifying results on the energy/cost saving potentials*, in fact, despite decades of research and great advances made in the field of BACS, the quantified results on the energy/cost saving potentials are vastly different making it hard to find the real impact of ACS under different boundary conditions and variables.
- *Unstructured information related to control hypothesis/boundary conditions/variables*, the available information is usually generic, and more details need to be provided. Therefore, a comprehensive framework is required to be developed to address this research gap.
- *Retrieval of accurate input data*, for instance, the locations of sensors can impact the accuracy and reliability of the retrieved data. There are only a few works that report on this critical subject and through studies are required to address this gap which will be otherwise a vulnerable point of ACS.
- *Selection of appropriate prediction/control horizon*, the current literature review revealed that prediction/horizon control could have an impact on the performance of ACS in the

building/HVAC system. In particular, there is little information on the relationship between the prediction horizon and the control horizon and saving. Thus, more investigations are required to assess the correlation between prediction/control horizon and various building boundary conditions for optimal energy and cost saving outcomes.

Among several ACS which have been developed, MPC has found a great deal of attention. However, this approach is less effective with unpredicted external disturbance and time-dependent input variables. The evolution in the building control systems has led to more advanced but also more sophisticated control solutions. The so-called APCS approach seems to be one of the most efficient control systems which can deal with deviations in the system operation, uncertainties and disturbance through self-adjustment and optimization for residential/tertiary buildings. APCS utilizes online optimization through a dynamic model of the system to compute an optimal sequence of parameters as inputs to minimize the prediction error of future values for an objective function. Yet the main open challenges regarding APCS can be listed as the following:

- *Implementing in real cases*, given that APCS is a fairly new concept introduced in recent years, implementation of this control strategy in real cases remains still challenging and needs further study to produce reliable results for an efficient application in the building sector and its' HVAC system. Moreover, the participation in demand response programs can make this technology useful to unlock building-to-grid interactions and to make APCS attractive from the business case point of view.
- *Demonstrating an accurate model of occupancy behaviour* is another open challenge in the context of APCS to obtain more precise predictions. In fact, occupancy behaviour can be only partially monitored through sensors (e.g. shading system control, presence, windows/doors opening), and cultural/sociological characteristics that deeply affect the actual human behaviour remain hidden or difficult to model.
- *Imposing eco-friendly behaviour through APCS*, another challenge is how to impose eco-friendly behaviour through APCS. While this could be partially done by direct controlling of HVAC components, enforcing occupants to follow eco-friendly behaviour through control actions remains a complex problem both from an implementation and cultural point of view.
- *Applying of APCS in the residential sector*, further research is needed to investigate the application of APCS in the residential sector, which doesn't have fixed pre-defined occupancy schedules, with a consequent increase of uncertainty factors for the control system. Nevertheless, to extend the penetration of APCS controller in this market, further developments are needed to implement APCS in a cheap hardware application and to develop common communication protocols to enable the connection and management of several buildings at the aggregated level.
- *Evaluating the feasibility of application of APCS*, can be difficult due to the assessment of the practical implementation of APCS on complex configurations of HVAC systems with several components that have interactions with each other. Moreover, the potential of HVAC flexibility can be limited by restrictions in the temporal rate of temperature changes that affect occupant thermal comfort.

In spite of challenges associated with APCS, intensive researches are being conducted to find appropriate solutions. In line with these researches, significant advancements have been made especially as more intelligent technologies such as cloud computing and IoT are being developed. Integration of such technologies with APCS can make it a more powerful and effective system of energy management in SB. As previously mentioned, the best configuration for APCS is the

simultaneous implementation of local at the building level and cloud-based for centralizing different information and transmission of data to the local controller. Nonetheless, this strategy needs to be implemented in real case scenarios to find technical gaps and resolve the challenges.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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

Acknowledgements

This study is financially supported by EU Research and Innovation Programme Horizon 2020 through number 768921 – HEART. The authors would like to thank the European Commission to enable the funding of this project.

Reference

- ABB. (2020). ABB. Retrieved March 23, 2020, from <https://new.abb.com/news/detail/57865/abb-adds-cylon-controls-to-its-smart-buildings-portfolio>
- Afram, A., & Janabi-Sharifi, F. (2014). Theory and applications of HVAC control systems - A review of model predictive control (MPC). *Building and Environment*, 72, 343–355. <https://doi.org/10.1016/j.buildenv.2013.11.016>
- Afram, A., Janabi-Sharifi, F., Fung, A. S., & Raahemifar, K. (2017). Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system. *Energy and Buildings*, 141, 96–113. <https://doi.org/10.1016/j.enbuild.2017.02.012>
- Aghemo, C., Blaso, L., & Pellegrino, A. (2014). Building automation and control systems : A case study to evaluate the energy and environmental performances of a lighting control system in of fi ces. *Automation in Construction*, 43, 10–22. <https://doi.org/10.1016/j.autcon.2014.02.015>
- Ahmadi-Karvigh, S., Becerik-Gerber, B., & Soibelman, L. (2019). Intelligent adaptive Automation: A framework for an activity-driven and user-centered building automation. *Energy and Buildings*, 188–189, 184–199. <https://doi.org/10.1016/j.enbuild.2019.02.007>
- Antonin van de Bree, Bernhard von Manteuffel, Lou Ramaekers, M. O. (2014). Role of Building Automation related to Renewable Energy in nZEB's. *Project Report*.
- Aste, N., Manfren, M., & Marenzi, G. (2017). Building Automation and Control Systems and performance optimization: A framework for analysis. *Renewable and Sustainable Energy Reviews*, 75(October 2016), 313–330. <https://doi.org/10.1016/j.rser.2016.10.072>
- Aswani, A., Master, N., Taneja, J., Krioukov, A., Culler, D., & Tomlin, C. (2012). *Energy-efficient building*

- HVAC control using hybrid system LBMPC. IFAC Proceedings Volumes (IFAC-PapersOnline)* (Vol. 4). IFAC. <https://doi.org/10.3182/20120823-5-NL-3013.00069>
- Avci, M., Erkoç, M., Rahmani, A., & Asfour, S. (2013). Model predictive HVAC load control in buildings using real-time electricity pricing. *Energy and Buildings*, 60, 199–209. <https://doi.org/10.1016/j.enbuild.2013.01.008>
- Barzin, R., Chen, J. J. J., Young, B. R., & Farid, M. M. (2016). Application of weather forecast in conjunction with price-based method for PCM solar passive buildings - An experimental study. *Applied Energy*, 163, 9–18. <https://doi.org/10.1016/j.apenergy.2015.11.016>
- Behrooz, F., Mariun, N., Marhaban, M. H., Radzi, M. A. M., & Ramli, A. R. (2018). Review of control techniques for HVAC systems-nonlinearity approaches based on fuzzy cognitive maps. *Energies*, 11(3). <https://doi.org/10.3390/en11030495>
- Biyik, E., Brooks, J. D., Sehgal, H., Shah, J., & Genc, S. (2015). Cloud-based Model Predictive Building Thermostatic Controls of Commercial Buildings: Algorithm and Implementation, 1683–1688. <https://doi.org/10.1109/ACC.2015.7170975>
- Biyik, E., & Kahraman, A. (2019). A predictive control strategy for optimal management of peak load , thermal comfort , energy storage and renewables in multi-zone buildings. *Journal of Building Engineering*, 25(June), 100826. <https://doi.org/10.1016/j.jobee.2019.100826>
- BuildingControls. (2016). Efficient Grid Connected Buildings: A Distributed Control Framework for Managing Flexible Loads | BuildingControls Project | H2020 | CORDIS | European Commission. Retrieved March 23, 2020, from <https://cordis.europa.eu/project/id/708984>
- Buonomano, A., Montanaro, U., Palombo, A., & Santini, S. (2015). Adaptive control for building thermo-hygrometric analysis: A novel dynamic simulation code for indoor spaces with multi-enclosed thermal zones. *Energy Procedia*, 78, 2190–2195. <https://doi.org/10.1016/j.egypro.2015.11.316>
- Candanedo, J. A., & Athienitis, A. K. (2011). Predictive control of radiant floor heating and solar-source heat pump operation in a solar house. *HVAC and R Research*, 17(3), 235–256. <https://doi.org/10.1080/10789669.2011.568319>
- Cao, X., Chen, J., Xiao, Y., & Sun, Y. (2010). Building-environment control with wireless sensor and actuator networks: Centralized versus distributed. *IEEE Transactions on Industrial Electronics*, 57(11), 3596–3605. <https://doi.org/10.1109/TIE.2009.2029585>
- Carrascal-Lekunberri, E., Garrido, I., Van Der Heijde, B., Garrido, A. J., Sala, J. M., & Helsen, L. (2017). Energy conservation in an office building using an enhanced blind system control. *Energies*, 10(2). <https://doi.org/10.3390/en10020196>
- Carrascal, E., Garrido, I., Garrido, A. J., & Sala, J. M. (2016). Optimization of the heating system use in aged public buildings via Model Predictive Control. *Energies*, 9(4). <https://doi.org/10.3390/en9040251>
- Coates, A., Hammoudeh, M., & Holmes, K. G. (2017). Internet of Things for Buildings Monitoring, 38. <https://doi.org/10.1145/3102304.3102342>
- Corbin, C. D., & Henze, G. P. (2017). Predictive control of residential HVAC and its impact on the grid. Part I: simulation framework and models. *Journal of Building Performance Simulation*, 10(3), 294–312. <https://doi.org/10.1080/19401493.2016.1231220>
- Cylon Controls Ltd. (2019). Cylon Controls. Retrieved March 23, 2020, from <https://www.cylon.com/>

- D'Agostino, D., Zangheri, P., Cuniberti, B., Paci, D., & Bertoldi, P. (2016). *Synthesis Report on the National Plans for NZEBs*. <https://doi.org/10.2790/659611>
- D'Ettorre, F., Conti, P., Schito, E., & Testi, D. (2019). Model predictive control of a hybrid heat pump system and impact of the prediction horizon on cost-saving potential and optimal storage capacity. *Applied Thermal Engineering*, *148*(November 2018), 524–535. <https://doi.org/10.1016/j.applthermaleng.2018.11.063>
- Dar, U. I., Sartori, I., Georges, L., & Novakovic, V. (2014). Advanced control of heat pumps for improved flexibility of Net-ZEB towards the grid. *Energy and Buildings*, *69*, 74–84. <https://doi.org/10.1016/j.enbuild.2013.10.019>
- De Wilde, P. (2018). *Building Performance Analysis*. John Wiley & Sons (Vol. 53). <https://doi.org/10.1017/CBO9781107415324.004>
- Dikel, E. E., Newsham, G. R., Xue, H., & Valdés, J. J. (2018). Potential energy savings from high-resolution sensor controls for LED lighting. *Energy & Buildings*, *158*, 43–53. <https://doi.org/10.1016/j.enbuild.2017.09.048>
- Dong, J., Olama, M. M., Kuruganti, T., Nutaro, J., Xue, Y., Sharma, I., & Djouadi, S. M. (2018). Adaptive building load control to enable high penetration of solar photovoltaic generation. *IEEE Power and Energy Society General Meeting, 2018-Janua*, 1–5. <https://doi.org/10.1109/PESGM.2017.8274533>
- Dounis, A. I., & Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment-A review. *Renewable and Sustainable Energy Reviews*, *13*(6–7), 1246–1261. <https://doi.org/10.1016/j.rser.2008.09.015>
- Drgoňa, J., Picard, D., Kvasnica, M., & Helsen, L. (2018). Approximate model predictive building control via machine learning. *Applied Energy*, *218*(March), 199–216. <https://doi.org/10.1016/j.apenergy.2018.02.156>
- Enervalis. (2018). Enervalis – Enabling a 100% green society. Retrieved March 23, 2020, from <https://www.enervalis.com/>
- European Commission. (2019a). COMMISSION RECOMMENDATION (EU) 2019/786 of 8 May 2019 on building renovation (notified under document C(2019) 3352), *6*(2015), 34–79.
- European Commission. (2019b). CT6 Smart Buildings - epbd-ca.eu. Retrieved November 20, 2019, from <https://epbd-ca.eu/topics-teams/topics/ct-6-smart-buildings>
- Eurostat. (2018). Early estimates of CO2 emissions from energy use In 2017, CO2 emissions in the EU estimated to have increased compared with 2016, (May), 2016–2017.
- Federico M. Butera, Morello Eugenio, Pastore Maria Chiara, & Fabrizio, L. (2018). *Energy and Resource Efficient Urban Neighbourhood Design Principles for Tropical Countries, practitioner's guidebook*.
- Ferreira, P. M., Ruano, A. E., Silva, S., & Conceição, E. Z. E. (2012). Neural networks based predictive control for thermal comfort and energy savings in public buildings. *Energy and Buildings*, *55*, 238–251. <https://doi.org/10.1016/j.enbuild.2012.08.002>
- Fielsch, S., Grunert, T., Stursberg, M., & Kummert, A. (2017). Model Predictive Control for Hydronic Heating Systems in Residential Buildings. *IFAC-PapersOnLine*, *50*(1), 4216–4221. <https://doi.org/10.1016/j.ifacol.2017.08.817>
- FP4-NNE-JOULE C EU program. (1998). Fuzzy controllers and smart tuning techniques for energy efficiency and overall performance of hvac systems in buildings | Project | FP4 | CORDIS | European

- Commission. Retrieved March 22, 2020, from <https://cordis.europa.eu/project/id/JOE3980090>
- FP7-PEOPLE program. (2014). Stochastic Model Predictive Control, Energy Efficient Building Control, Smart Grid | SMPCBCSG Project | FP7 | CORDIS | European Commission. Retrieved March 23, 2020, from <https://cordis.europa.eu/project/id/302255>
- Guestrin, C. (2005). Resource-Aware Wireless Sensor-Actuator Networks, (January).
- Gyalistras, D., & Division, B. T. (2010). *Use of Weather and Occupancy Forecasts For Optimal Building Climate Control (OptiControl): Two Years Progress Report*.
- H2020 BuildHeat project. (2019). BuildHeat. Retrieved March 23, 2020, from <http://www.buildheat.eu/>
- H2020 project HYBUILD. (2013). HYBUILD – Innovative compact hybrid storage systems for low energy buildings. Retrieved March 23, 2020, from <http://www.hybuild.eu/>
- H2020 project REWARDHeat. (2020). Renewable and Waste Heat Recovery for Competitive District Heating and Cooling Networks | REWARDHeat Project | H2020 | CORDIS | European Commission. Retrieved March 23, 2020, from <https://cordis.europa.eu/project/id/857811>
- H2020 projects Sim4Blocks. (2017). Sim4Blocks - European Project. Retrieved from <https://www.sim4blocks.eu/>
- Hazyuk, I., Ghiaus, C., & Penhouet, D. (2014). Model Predictive Control of thermal comfort as a benchmark for controller performance. *Automation in Construction*, 43, 98–109. <https://doi.org/10.1016/j.autcon.2014.03.016>
- Henze, G. P., Felsmann, C., & Knabe, G. (2004). Evaluation of optimal control for active and passive building thermal storage. *International Journal of Thermal Sciences*, 43(2), 173–183. <https://doi.org/10.1016/j.ijthermalsci.2003.06.001>
- HIT2GAP. (2016). HIT2GAP. Retrieved March 23, 2020, from <http://www.hit2gap.eu/about-the-project/bemserver>
- Huang, H., Chen, L., & Hu, E. (2015). A new model predictive control scheme for energy and cost savings in commercial buildings: An airport terminal building case study. *Building and Environment*, 89, 203–216. <https://doi.org/10.1016/j.buildenv.2015.01.037>
- Javed, A., Larijani, H., Ahmadiania, A., Emmanuel, R., Mannion, M., & Gibson, D. (2017). Design and Implementation of a Cloud Enabled Random Neural Network-Based Decentralized Smart Controller with Intelligent Sensor Nodes for HVAC. *IEEE Internet of Things Journal*, 4(2), 393–403. <https://doi.org/10.1109/JIOT.2016.2627403>
- Kavgic, M., Hilliard, T., & Swan, L. (2015). Opportunities for implementation of MPC in commercial buildings. *Energy Procedia*, 78, 2148–2153. <https://doi.org/10.1016/j.egypro.2015.11.300>
- Kelman, A., Ma, Y., & Borrelli, F. (2011). Analysis of Local Optima in Predictive Control for Energy Efficient Buildings. *2011 50th IEEE Conference on Decision and Control and European Control Conference*, 5125–5130. <https://doi.org/10.1109/CDC.2011.6161498>
- Kolokotsa, D., Pouliezios, A., Stavrakakis, G., & Lazos, C. (2009). Predictive control techniques for energy and indoor environmental quality management in buildings. *Building and Environment*, 44(9), 1850–1863. <https://doi.org/10.1016/j.buildenv.2008.12.007>
- Kolokotsa, D., Rovas, D., Kosmatopoulos, E., & Kalaitzakis, K. (2011). A roadmap towards intelligent net zero- and positive-energy buildings. *Solar Energy*, 85(12), 3067–3084. <https://doi.org/10.1016/j.solener.2010.09.001>

- Kusiak, A., Xu, G., & Tang, F. (2011). Optimization of an HVAC system with a strength multi-objective particle-swarm algorithm. *Energy*, *36*(10), 5935–5943. <https://doi.org/10.1016/j.energy.2011.08.024>
- Lauro, F., Longobardi, L., & Panziera, S. (2014). An adaptive distributed predictive control strategy for temperature regulation in a multizone office building. *Proceedings - 2014 IEEE International Workshop on Intelligent Energy Systems, IWIES 2014*, 32–37. <https://doi.org/10.1109/IWIES.2014.6957043>
- Le Dréau, J., & Heiselberg, P. (2016). Energy flexibility of residential buildings using short term heat storage in the thermal mass. *Energy*, *111*, 991–1002. <https://doi.org/10.1016/j.energy.2016.05.076>
- Lee, Y. M., Horesh, R., & Liberti, L. (2015). Optimal HVAC control as demand response with on-site energy storage and generation system. *Energy Procedia*, *78*, 2106–2111. <https://doi.org/10.1016/j.egypro.2015.11.253>
- Li, W., Zhang, J., & Zhao, T. (2019). Indoor thermal environment optimal control for thermal comfort and energy saving based on online monitoring of thermal sensation. *Energy & Buildings*, *197*, 57–67. <https://doi.org/10.1016/j.enbuild.2019.05.050>
- Liu, M., & Heiselberg, P. (2019). Energy flexibility of a nearly zero-energy building with weather predictive control on a convective building energy system and evaluated with different metrics. *Applied Energy*, *233–234*(October 2018), 764–775. <https://doi.org/10.1016/j.apenergy.2018.10.070>
- Lu, Y., Wang, S., & Shan, K. (2015). Design optimization and optimal control of grid-connected and standalone nearly/net zero energy buildings. *Applied Energy*, *155*, 463–477. <https://doi.org/10.1016/j.apenergy.2015.06.007>
- Luzi, M., Vaccarini, M., & Lemma, M. (2019). A tuning methodology of Model Predictive Control design for energy efficient building thermal control. *Journal of Building Engineering*, *21*(March 2018), 28–36. <https://doi.org/10.1016/j.jobee.2018.09.022>
- Ma, J., Qin, J., Salsbury, T., & Xu, P. (2012). Demand reduction in building energy systems based on economic model predictive control. *Chemical Engineering Science*, *67*(1), 92–100. <https://doi.org/10.1016/j.ces.2011.07.052>
- Ma, Y., Borrelli, F., Hancey, B., Coffey, B., Bengesa, S., & Haves, P. (2010). Model Predictive Control for the Operation of Building Cooling Systems. *Proceedings of the 2010 American Control Conference*, 5106–5111. <https://doi.org/10.1109/ACC.2010.5530468>
- Ma, Y., Kelman, A., Daly, A., & Borrelli, F. (2012). Energy Efficient Buildings with Thermal Storage. *IEEE Control Systems*, *32*(FEBRUARY), 44–64. <https://doi.org/10.1109/MCS.2011.2172532>
- Maasoumy, M., Razmara, M., Shahbakhti, M., & Vincentelli, A. S. (2014). Handling model uncertainty in model predictive control for energy efficient buildings. *Energy and Buildings*, *77*, 377–392. <https://doi.org/10.1016/j.enbuild.2014.03.057>
- Maasoumy, Mehdi, & Sangiovanni-Vincentelli, A. (2012). Optimal Control of Building HVAC Systems in the Presence of Imperfect Predictions, (November), 257. <https://doi.org/10.1115/dscc2012-movic2012-8523>
- Manjarres, D., Mera, A., Perea, E., Lejarazu, A., & Gil-Lopez, S. (2017). An energy-efficient predictive control for HVAC systems applied to tertiary buildings based on regression techniques. *Energy and Buildings*, *152*, 409–417. <https://doi.org/10.1016/j.enbuild.2017.07.056>
- Mařík, K., Rojíček, J., Stluka, P., & Vass, J. (2011). Advanced HVAC control: Theory vs. reality. *IFAC Proceedings Volumes (IFAC-PapersOnline)*, *44*(1 PART 1), 3108–3113.

<https://doi.org/10.3182/20110828-6-IT-1002.03085>

- Minoli, D., Sohraby, K., & Occhiogrosso, B. (2017). IoT Considerations, Requirements, and Architectures for Smart Buildings-Energy Optimization and Next-Generation Building Management Systems. *IEEE Internet of Things Journal*, 4(1), 269–283. <https://doi.org/10.1109/JIOT.2017.2647881>
- Mirinejad, H., Sadati, S. H., Ghasemian, M., & Torab, H. (2008). Control Techniques in Heating, Ventilating and Air Conditioning (HVAC) Systems. *Journal of Computer Science*, 4(9), 777–783. <https://doi.org/10.3844/jcssp.2008.777.783>
- Mizumoto, I., & Fujimoto, Y. (2012). Adaptive predictive control system design with an adaptive output estimator. *Proceedings of the IEEE Conference on Decision and Control*, 5434–5441. <https://doi.org/10.1109/CDC.2012.6426601>
- Moroşan, P. D., Bourdais, R., Dumur, D., & Buisson, J. (2010). Building temperature regulation using a distributed model predictive control. *Energy and Buildings*, 42(9), 1445–1452. <https://doi.org/10.1016/j.enbuild.2010.03.014>
- Nounou, H. N., & Nounou, M. N. (2011). Resilient Adaptive Control of Uncertain Time-Delay Systems, (1989).
- ODYS Srl. (2019). ODYS - Embedded MPC and real-time optimization for next-gen controls. Retrieved March 23, 2020, from <http://www.odys.it/>
- Oldewurtel, F., Parisio, A., Jones, C. N., Morari, M., Gyalistras, D., Gwerder, M., ... Wirth, K. (2010). Energy efficient building climate control using Stochastic Model Predictive Control and weather predictions, (August), 5100–5105. <https://doi.org/10.1109/acc.2010.5530680>
- Oldewurtel, Frauke, Parisio, A., Jones, C. N., Gyalistras, D., Gwerder, M., Stauch, V., ... Morari, M. (2012). Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, 45, 15–27. <https://doi.org/10.1016/j.enbuild.2011.09.022>
- Oldewurtel, Frauke, Roald, L., Andersson, G., & Tomlin, C. (2015). Adaptively constrained stochastic model predictive control applied to security constrained optimal power flow. *2015 American Control Conference (ACC)*, (c), 931–936. <https://doi.org/10.1109/ACC.2015.7170853>
- Perera, D. W. U., Pfeiffer, C., & Skeie, N.-O. (2014). Control of temperature and energy consumption in buildings - A review. *Igarss 2014*, 5(1), 1–5.
- Png, E., Srinivasan, S., Bekiroglu, K., Chaoyang, J., Su, R., & Poolla, K. (2019). An internet of things upgrade for smart and scalable heating, ventilation and air-conditioning control in commercial buildings. *Applied Energy*, 239(January), 408–424. <https://doi.org/10.1016/j.apenergy.2019.01.229>
- Ponds, K. T., Arefi, A., Sayigh, A., & Ledwich, G. (2018). Aggregator of Demand Response for Renewable Integration and Customer Engagement : Strengths ., <https://doi.org/10.3390/en11092391>
- QCoefficient Inc. (2017). QCoefficient. Retrieved March 23, 2020, from <http://qcoefficient.com/>
- Rajith, A. (2018). Real-time Optimized HVAC Control System on top of an IoT Framework. *2018 Third International Conference on Fog and Mobile Edge Computing (FMEC)*, 181–186. <https://doi.org/10.1109/FMEC.2018.8364062>
- REnnovates. (2011). REnnovates – a holistic systemic deep renovation concept. Retrieved March 23, 2020, from <https://rennovates.eu/>
- Rockett, P., & Hathway, E. A. (2017). Model-predictive control for non-domestic buildings: a critical review and prospects. *Building Research and Information*, 45(5), 556–571.

<https://doi.org/10.1080/09613218.2016.1139885>

- Royapoor, M., Antony, A., & Roskilly, T. (2018). A review of building climate and plant controls, and a survey of industry perspectives. *Energy and Buildings*, 158, 453–465. <https://doi.org/10.1016/j.enbuild.2017.10.022>
- Sakunthala, S., & Mandadi, P. N. (2018). Soft Computing Techniques and Applications in Electrical Drives Fuzzy logic , and Genetic Algorithm, 8(2), 3285–3289. <https://doi.org/10.29042/2018-3285-3289>
- Sala-Cardoso, E., Delgado-Prieto, M., Kampouropoulos, K., & Romeral, L. (2018). Activity-aware HVAC power demand forecasting. *Energy and Buildings*, 170, 15–24. <https://doi.org/10.1016/j.enbuild.2018.03.087>
- Schmelas, M., Feldmann, T., Wellnitz, P., & Bollin, E. (2016). Adaptive predictive control of thermo-active building systems (TABS) based on a multiple regression algorithm: First practical test. *Energy and Buildings*, 129, 367–377. <https://doi.org/10.1016/j.enbuild.2016.08.013>
- Serale, G., Fiorentini, M., Capozzoli, A., Bernardini, D., & Bemporad, A. (2018). Model Predictive Control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. *Energies*, 11(3). <https://doi.org/10.3390/en11030631>
- Shan, K., Wang, S., Yan, C., & Xiao, F. (2016). Building demand response and control methods for smart grids: A review. *Science and Technology for the Built Environment*, 22(6), 692–704. <https://doi.org/10.1080/23744731.2016.1192878>
- Shi, J., Yu, N., & Yao, W. (2017). Energy Efficient Building HVAC Control Algorithm with Real-time Occupancy Prediction. *Energy Procedia*, 111, 267–276. <https://doi.org/10.1016/J.EGYPRO.2017.03.028>
- Short, M. (2012). Real-time infinite horizon adaptive/predictive control for Smart home HVAC applications. *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, 1–8. <https://doi.org/10.1109/ETFA.2012.6489677>
- Siemens. (2011). *Desigo - Building Automation System*.
- Siemens. (2016). Siemens and IBM collaborate on building technology - Products And Services. Retrieved March 23, 2020, from <https://www.constructionweekonline.com/article-37718-siemens-and-ibm-collaborate-on-building-technology>
- SMARTCIM. (2015). Smart interoperable electronic active valve, control eco-system and service to achieve superior building efficiency and user awareness | SMARTCIM Project | H2020 | CORDIS | European Commission. Retrieved March 23, 2020, from <https://cordis.europa.eu/project/id/684086>
- Stauffer, Y., Olivero, E., Onillon, E., Mahmed, C., & Lindelöf, D. (2017). NeuroCool: Field tests of an adaptive, model-predictive controller for HVAC systems. *Energy Procedia*, 122, 127–132. <https://doi.org/10.1016/j.egypro.2017.07.316>
- Stluka, P., Mařík, K., & Endel, P. (2014). Advanced control solutions for building systems. *IFAC Proceedings Volumes (IFAC-PapersOnline)*, 19(August), 606–611.
- Subbaram Naidu, D., & Rieger, C. G. (2011a). Advanced control strategies for heating, ventilation, air-conditioning, and refrigeration systems - An overview: Part I: Hard control. *HVAC and R Research*, 17(1), 2–21. <https://doi.org/10.1080/10789669.2011.540942>
- Subbaram Naidu, D., & Rieger, C. G. (2011b). Advanced control strategies for HVAC&R systems - An overview: Part II: Soft and fusion control. *HVAC and R Research*, 17(2), 144–158.

<https://doi.org/10.1080/10789669.2011.555650>

- Tanaskovic, M., Sturzenegger, D., Smith, R., & Morari, M. (2017). Robust Adaptive Model Predictive Building Climate Control. *IFAC-PapersOnLine*, 50(1), 1871–1876. <https://doi.org/10.1016/j.ifacol.2017.08.257>
- Tang, Y., & Chen, X. (2019). Research on Control Metherm of Adaptive Lighting system in Intelligent Building, 1–5.
- Tesfay, M., Alsaleem, F., Arunasalam, P., & Rao, A. (2018). Adaptive-model predictive control of electronic expansion valves with adjustable setpoint for evaporator superheat minimization. *Building and Environment*, 133(December 2017), 151–160. <https://doi.org/10.1016/j.buildenv.2018.02.015>
- Thieblemont, H., Haghghat, F., Ooka, R., & Moreau, A. (2017). Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the art. *Energy and Buildings*, 153, 485–500. <https://doi.org/10.1016/j.enbuild.2017.08.010>
- Vafamehr, A., & Khodayar, M. E. (2018). Energy-aware cloud computing. *Electricity Journal*, 31(2), 40–49. <https://doi.org/10.1016/j.tej.2018.01.009>
- Viot, H., Sempey, A., Mora, L., Batsale, J. C., & Malvestio, J. (2018). Model predictive control of a thermally activated building system to improve energy management of an experimental building : Part II - Potential of predictive strategy. *Energy & Buildings*, 172, 385–396. <https://doi.org/10.1016/j.enbuild.2018.04.062>
- Wang, S., & Ma, Z. (2008). Supervisory and optimal control of building HVAC systems: A review. *HVAC and R Research*, 14(1), 3–32. <https://doi.org/10.1080/10789669.2008.10390991>
- Wei, C., & Li, Y. (2011). Design of energy consumption monitoring and energy-saving management system of intelligent building based on the Internet of things. *2011 International Conference on Electronics, Communications and Control, ICECC 2011 - Proceedings*, 3650–3652. <https://doi.org/10.1109/ICECC.2011.6066758>
- Wen, J. T. (2018). *Advances in Industrial Control Intelligent Building Control Systems A Survey of Modern Building Control and Sensing Strategies*. Retrieved from <http://www.springer.com/series/1412>
- Xu, L., Wang, S., & Xiao, F. (2019). An adaptive optimal monthly peak building demand limiting strategy considering load uncertainty. *Applied Energy*, 253(July), 113582. <https://doi.org/10.1016/j.apenergy.2019.113582>
- Xu, M., & Li, S. (2007). Practical generalized predictive control with decentralized identification approach to HVAC systems. *Energy Conversion and Management*, 48(1), 292–299. <https://doi.org/10.1016/j.enconman.2006.04.012>
- Yan, Y., Zhou, J., Lin, Y., Yang, W., Wang, P., & Zhang, G. (2008). Adaptive optimal control model for building cooling and heating sources. *Energy and Buildings*, 40(8), 1394–1401. <https://doi.org/10.1016/j.enbuild.2008.01.003>
- Yang, S., Pun, M., Chen, W., Feng, B., & Zhai, D. (2019). An adaptive robust model predictive control for indoor climate optimization and uncertainties handling in buildings. *Building and Environment*, 163(May), 106326. <https://doi.org/10.1016/j.buildenv.2019.106326>
- Yang, Z., & Becerik-Gerber, B. (2016). How does building occupancy influence energy efficiency of HVAC systems? *Energy Procedia*, 88, 775–780. <https://doi.org/10.1016/j.egypro.2016.06.111>
- Yu, Z., Huang, G., Haghghat, F., Li, H., & Zhang, G. (2015). Control strategies for integration of thermal

energy storage into buildings: State-of-the-art review. *Energy and Buildings*, 106, 203–215.
<https://doi.org/10.1016/j.enbuild.2015.05.038>

Zhoua Beiyan, J. C. and R. S. (2018). A load-adaptive and predictive control of energy-efficient building automation in production environment. *Procedia CIRP*, 79, 245–250.
<https://doi.org/10.1016/j.procir.2019.02.058>

Journal Pre-proof

Table 1. Main pros and cons of Traditional Control strategies (TCS)

| Control strategy | Pros | Cons |
|------------------|---|---|
| TCS | <p>Simple structure (Behrooz et al., 2018)(Perera, Pfeiffer, & Skeie, 2014). Quick response (Perera et al., 2014). Easy implementation (Behrooz et al., 2018). Low initial cost (Behrooz et al., 2018)(Perera et al., 2014).</p> | <p>Low accuracy/quality/performance/energy efficiency (Behrooz et al., 2018)(Perera et al., 2014) Accept only binary inputs (Behrooz et al., 2018) Not proper for control non-linear moving processes with time delays, complex system with uncertain information system (Behrooz et al., 2018) High maintenance cost (Perera et al., 2014) Not capable of implementing dynamic information/input (Lee et al., 2015) Not proper for high thermal inertia systems, building envelop and technical elements (Afram & Janabi-Sharifi, 2014) Incapable to interact with external environment (i.e. user/grid/district/city) Incapable of regulating/adapting the input variables (e.g. setpoints, schedules, working modes) accurately</p> |

Table 2. Main pros and cons of Model Predictive Control (MPC)

| Control strategy | Pros | Cons |
|------------------|--|--|
| MPC | <p>Energy/Cost effective (Serale et al., 2018). Handle processes with time delays (Perera et al., 2014). High computational power (Serale et al., 2018)(Thieblemont et al., 2017). Disturbance robustness (Thieblemont et al., 2017)(Behrooz et al., 2018). Peak load shifting/shaving/matching (Lu, Wang, & Shan, 2015)(Biyik & Kahraman, 2019). Better regulation of input parameters (Moroşan, Bourdais, Dumur, & Buisson, 2010). Control of multiple variables (Perera et al., 2014). Future disturbances/control actions prediction (Behrooz et al., 2018). Exploits an accurate building dynamic model (Drgoňa, Picard, Kvasnica, & Helsen, 2018). Capable to integrate with thermal mass building (Serale et al., 2018).</p> | <p>Need improvement of mathematical/analytical model of the building (Perera et al., 2014). Expensive installation (Behrooz et al., 2018). Incapable of handling uncertain disturbances.</p> |

Table 3. Main pros and cons of Adaptive control strategies.

| Control strategy | Pros | Cons |
|------------------|---|--|
| Adaptive | <p>Energy/Cost effective (Perera et al., 2014). Handle non-linear processes with time delays (Perera et al., 2014). Quick response to changes in process dynamics (Behrooz et al., 2018). Fast regulation of input parameters (Dounis & Caraiscos, 2009). Able to self-regulate/adapt to parameters' changes (Dounis & Caraiscos, 2009). Capable of handling uncertain disturbances (M. Maasoumy et al., 2014)</p> | <p>Need improvement of mathematical/analytical model of the building (Behrooz et al., 2018).</p> |

Table 4. Main pros and cons of Adaptive Predictive Control Strategies (APCS)

| Control strategy | Pros | Cons |
|------------------|--|--|
| APCS | <p>Energy/Cost effective (D'Ettorre et al., 2019) (Stauffer, Olivero, Onillon, Mahmed, & Lindelöf, 2017). Applicable for the nonlinear models and the systems with slowly time-varying or uncertain variables (Behrooz et al., 2018). Improve the flexibility of the system (Buonomano et al., 2015). Peak load shifting/shaving/matching capability (Liu & Heiselberg, 2019) (J. Ma et al., 2012). Reduction in fluctuations from a setpoint (Moroşan et al., 2010). Quick response to changes in process dynamics (Perera et al., 2014) (Kavgic, Hilliard, & Swan, 2015). Control of multiple variables within bounds (M. Xu & Li, 2007). Capable of controlling thermo-active building systems (TABS) with high thermal inertia (Schmelas et al., 2016).</p> | <p>Require large computational liability, when the system has restrictions and constraints. A large number of parameters that need to be theoretically adjusted (Short, 2012).</p> |