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

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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.

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, Zangheri, Cuniberti, Paci, & Bertoldi, 2016; Kolokotsa, Rovas, Kosmatopoulos, & Kalaitzakis, 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, Eugenio, Chiara, & Fabrizio, 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, Sartori, Georges, & Novakovic, 2014; Subbaram Naidu & Rieger, 2011a). Thus, the utilization of automated technologies is

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Nomenclature

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

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, Manfren, & Marenzi, 2017). In fact, several recent studies showed that about half of utilized energy in buildings is consumed for the HVAC system (Lee, Horesh, & Liberti, 2015; Mařík, Rojíček, Stluka, & Vass, 2011; Shi, Yu, & Yao, 2017). 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, Sadati, Ghasemian, & Torab, 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, Fiorentini, Capozzoli, Bernardini, & Bemporad, 2018). However, its performance needs to be improved by adding more features. A suitable solution is the integration of MPC with adaptive control strategies (Tesfay, Alsaleem, Arunasalam, & Rao, 2018; Yang, Pun, Chen, Feng, & Zhai, 2019). 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, Blaso, & Pellegrino, 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, Ghiaus, & Penhouet, 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, & Zhao, 2019).
- *energy saving,* by applying techniques which ensure the minimum amount of energy without compromising thermal/visual comfort (Dikel, Newsham, Xue, & Valdés, 2018; Huang, Chen, & Hu, 2015; Manjarres, Mera, Perea, Lejarazu, & Gil-Lopez, 2017).
- *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)

(D'Ettorre, Conti, Schito, & Testi, 2019; Shan, Wang, Yan, & Xiao, 2016; Ma, Qin, Salsbury, & Xu, 2012).

- *optimal interaction with the external environment:* the external environment could be the district or the national grid.

Fig. 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 CO_2 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, Mariun, Marhaban, Radzi, & Ramli, 2018; Royapoor, Antony, & Roskilly, 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, CO_2, 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);

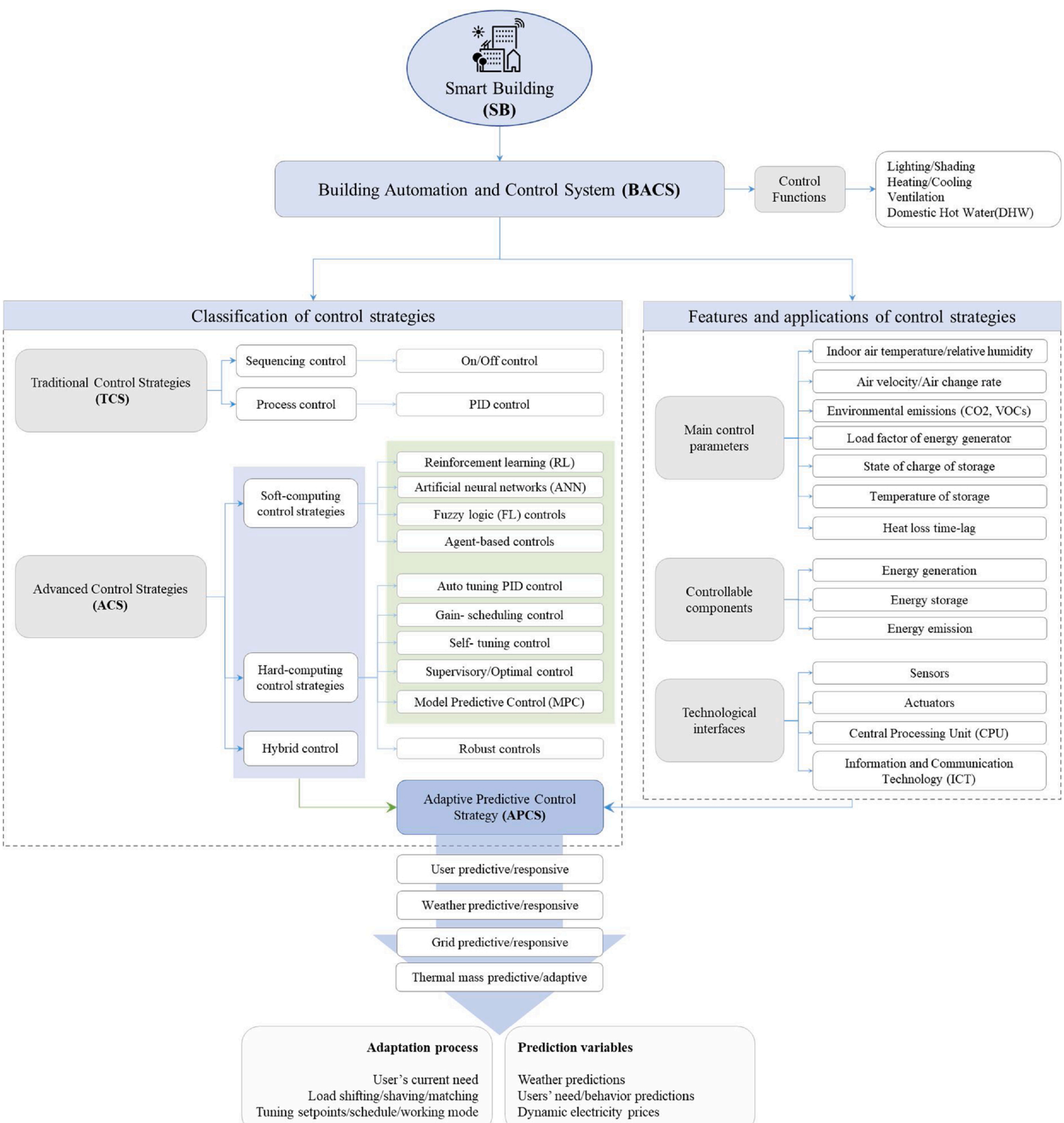

Fig. 1. Features, applications and functions of BACS in buildings and HVAC systems.

- 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.

The green box in Fig. 1 highlights adaptive control strategies. A control strategy is adaptive if employs mechanisms (e.g., self-tuning, relearning) 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 Fig. 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, Pfeiffer, & Skeie, 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, von Manteuffel, & Lou Ramaekers, 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 (Fig. 2).

Fig. 3 represents the field of applications of ACS in buildings

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

Control strategy	Pros	Cons
TCS	Simple structure (Behrooz et al., 2018; Perera et al., 2014).	Low accuracy/quality/performance/energy efficiency (Behrooz et al., 2018; Perera et al., 2014)
	Quick response (Perera et al., 2014).	Accept only binary inputs (Behrooz et al., 2018)
	Easy implementation (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)
	Low initial cost (Behrooz et al., 2018; Perera et al., 2014).	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

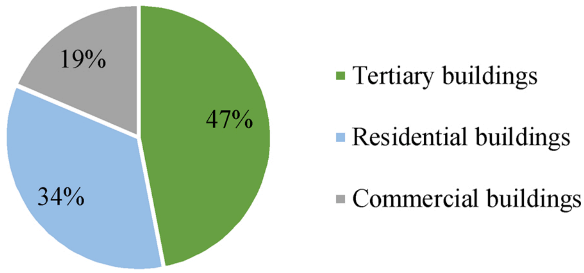

Fig. 2. Proportion of building typologies considered for applications of ACS in the literature retrieved from SCOPUS.

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 (Thieblemont, Haghighat, Ooka, & Moreau, 2017; Yu, Huang, Haghighat, Li, & Zhang, 2015) 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 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, Xu, & Tang's, 2011).

Fig. 4 represents different approaches of ACS applied in buildings and HVAC systems by researches 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.

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 (Hazyuk et al., 2014; Serale et al., 2018). 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 (Dounis & Caraiscos, 2009; Le Dréau & Heiselberg, 2016). 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, Felsmann, & Knabe, 2004) by means of sequential time block optimization over a horizon of 24 h.

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 (D'Ettorre et al., 2019; Luzi, Vaccarini, & Lemma, 2019). Although most of the

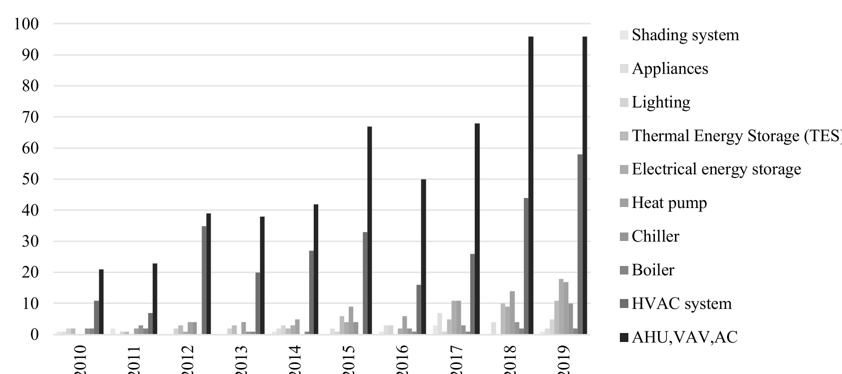

Fig. 3. Number of publications for field of applications of ACS in the literature retrieved from SCOPUS.

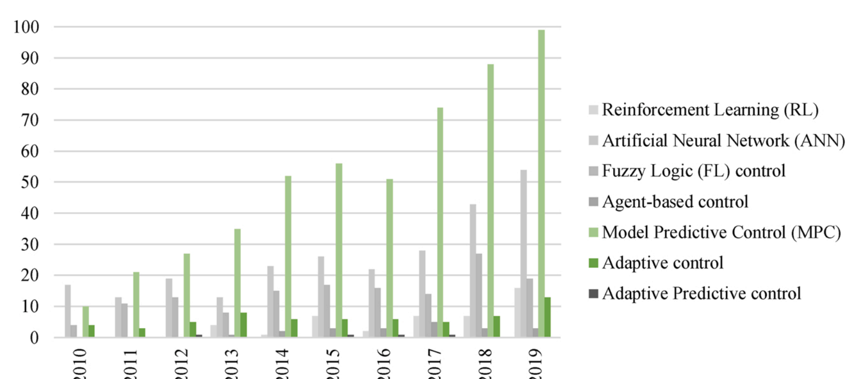

Fig. 4. Number of publications for different approaches of ACS in the literature retrieved from SCOPUS.

applications of predictive control are for tertiary buildings, (Fielsch, Grunert, Stursberg, & Kummert, 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, Pouliezos, Stavrakakis, & Lazos, 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. (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, (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, Chen, Young, & Farid, 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, Brooks, Sehgal, Shah, & Genc, 2015). Kelman, Ma, and Borrelli (2011) proposed an MPC approach in a typical commercial building for two common HVAC configurations to minimizes 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 & Becerik-Gerber, 2016). As claimed in (Ponds, Arefi, Sayigh, & Ledwich, 2018), the user interacts with the MPC to automatically create optimal load operation schedules, specifying different priorities and their comfort settings. Ahmadi-Karvigh, Becerik-Gerber, and Soibelman (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%–45% by adaptive automation of control system has resulted.
- *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, Feldmann, Wellnitz, & Bollin, 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 Fig. 5. As shown in this figure, weather forecast and building load prediction are the most common prediction data used in field of ACS.

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'Ettorre 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

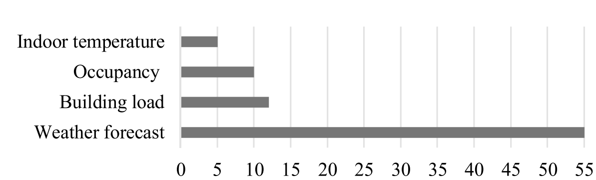

Fig. 5. Prediction data of ACS in the literature retrieved from SCOPUS.

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, Razmara, Shahbakhti, & Vincentelli, 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 (Liu & Heiselberg, 2019; Xu, Wang, & Xiao, 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 (Gyalistras & Division, 2010; Oldewurtel et al., 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 & Sangiovanni-Vincentelli, 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, Montanaro, Palombo, & Santini, 2015; Maasoumy et al., 2014; Mizumoto & Fujimoto, 2012) 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 Fig. 6 and discussed as in the following.

Residential sector: the highest thermal energy saving potential

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

Control strategy	Pros	Cons
MPC	Energy/Cost effective (Serale et al., 2018).	Need improvement of mathematical/analytical model of the building (Perera et al., 2014).
	Handle processes with time delays (Perera et al., 2014).	Expensive installation (Behrooz et al., 2018).
	High computational power (Serale et al., 2018; Thieblemont et al., 2017).	Incapable of handling uncertain disturbances.
	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)	

Table 3
Main pros and cons of Adaptive control strategies.

Control strategy	Pros	Cons
Adaptive	Energy/Cost effective (Perera et al., 2014).	Need improvement of mathematical/analytical model of the building (Behrooz et al., 2018).
	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)	

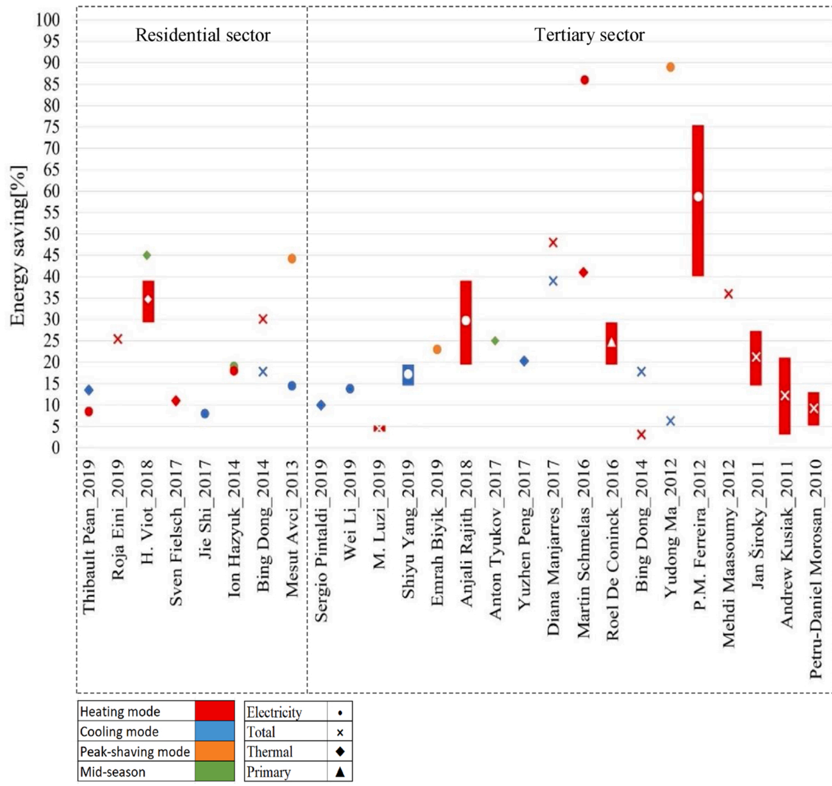

Fig. 6. Cost saving potential by application of ACS in the analyzed literature.

reported is 45 % in mid-season and 30%–40% in heating mode, respectively by comparison of MPC with two conventional control strategies in an experimental assessment (Viot, Sempey, Mora, Batsale, & Malvestio, 2018). For electrical energy consumption, (Avci, Erkoc, Rahmani, & Asfour, 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, Kelman, Daly, & Borrelli, 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, Ruano, Silva, & Conceição, 2012) in the range of 41%–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 Fig. 7. (Afram, Janabi-Sharifi, Fung, & Raahemifar, 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).

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 Figs. 6 and 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; Oldewurtel, Roald, Andersson, & Tomlin, 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

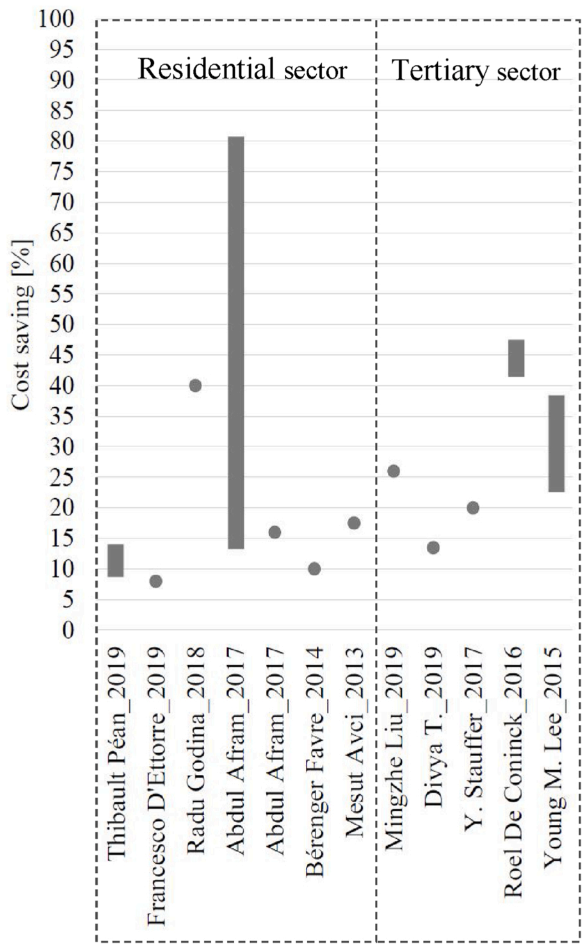

Fig. 7. Energy saving potential by applications of ACS in the analyzed literature.

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 (Siemens, 2016, 2011) to develop a cloud-based BEM system exploiting data analytics and IoT technologies. Desigo™ (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 m^2 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. (Tesfay 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 (Tesfay et al., 2018). Lauro, Longobardi, and Panzieri (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, Sturzenegger, Smith, & Morari, 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 it well suited for target systems including nonlinear processes, time delays, high dynamic and it can deal with uncertainty parameters

(Behrooz et al., 2018; Yang et al., 2019). 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 (Carrascal, Garrido, Garrido, & Sala, 2016; Le Dréau & Heiselberg, 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, Delgado-Prieto, Kampouropoulos, & Romeral, 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. Cao, Chen, Xiao, and Sun (2010), Coates, Hammoudeh, and Holmes (2017) and 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, Sohraby, & Occhiogrosso, 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. Fig. 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. 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; Zhou, Chikkala, & Schmitt, 2018). The applicability of prediction provides an online solution of optimal control problems, where tracking the prediction error is possible (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 (Hazyuk et al., 2014; Luzi et al., 2019). 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

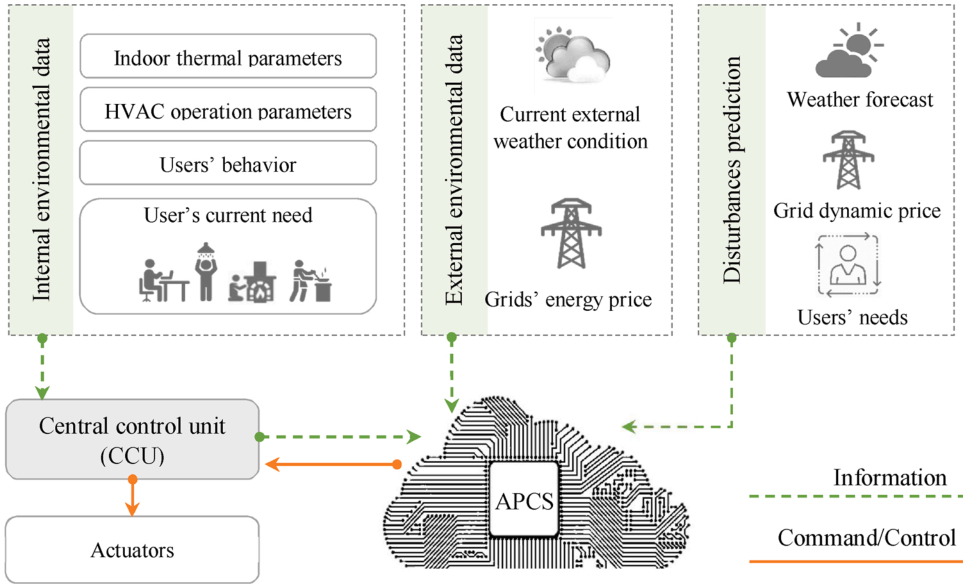

Fig. 8. Application of APCS as a supervisory control system through a cloud platform.

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

Control strategy	Pros	Cons
APCS	Energy/Cost effective (D'Ettorre et al., 2019; Stauffer, Olivero, Onillon, Mahmed, & Lindelöf, 2017).	Require large computational liability, when the system has restrictions and constraints. A large number of parameters that need to be theoretically adjusted (Short, 2012).
	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; Ma, Qin 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 (Xu & Li, 2007). Capable of controlling thermo-active building systems (TABS) with high thermal inertia (Schmelas et al., 2016).	

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.
- *Retrievement 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 trough 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 Competing Interest

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.

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