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The potential of building automation and control systems to lower the energy demand in residential buildings: a review of their performance and influencing parameters

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Abstract

Well-designed and properly implemented Building Automation and Control Systems (BACS) can contribute to a reduction of the energy consumption in buildings, while increasing comfort and convenience for the occupants. For design and planning purposes, there is a need to quantify the potential impacts of implementing BACS, especially related to their capability for reducing the operational energy demand of a building. The simplified BAC factor method defined in standard EN 15232 aims to provide a generic estimation of expected energy savings. Alternatively, dynamic energy performance simulations can provide more detailed insights on a particular building design.

Comparing energy savings from BACS in different sources in literature reveals significant discrepancies between various studies and assessment methods. This paper aims to clarify and discuss the differences between the various assessments and to identify the parameters that could affect BACS (i.e. heating, domestic hot water supply, lighting and shading control systems) performance in residential buildings. It is concluded that simplified methods as the EN 15232 BAC factor method do not provide a reliable estimate of achievable energy savings. The results obtained by more detailed simulations reported in literature show a significant variation in BACS performance. Two main causes are identified. Factors such as building and installation design parameters, occupant behaviour, context (e.g. climate) and baseline energy demand affect the energy saving potential but are not explicitly taken into account in the BAC factor method. Next, a significant part of the variation in reported energy saving potential can be attributed to discrepancies in modelling methods.

Highlights

- Relative energy saving due to BACS are sensitive to case-dependent parameters.
- Relative energy savings are higher when the absolute energy consumption is larger.
- BACS performances are often compared to an inappropriate reference scenario.
- Energy savings of BACS are overestimated in simulations due to modelling errors.
- EN 15232 BAC factor method is poorly suited to define BACS energy saving potential.

Keywords

BACS; BAC factor method; energy performance; heating control; DHW supply control; lighting control; shading control; energy management.

Word Count

9402 words

List of abbreviations including units and nomenclature

BAC	Building Automation and Control
BACS	Building Automation and Control System
BAS	Building Automation System
BEMS	Building Energy Management System
BMS	Building Management System
DHW	Domestic Hot Water
EMS	Energy Management System
EPB	Energy Performance of Buildings
EPBD	Energy Performance of Buildings Directive
EU	European Union
HVAC	Heating, Ventilation and Air Conditioning
KPI	Key Performance Indicator
RES	Renewable Energy Sources
SBA	Smart Buildings Alliance
SRI	Smart Readiness Indicator
TBM	Technical Building Management
TES	Thermal Energy Storage
WWR (-)	Window to Wall Ratio

1 Introduction

Reducing the energy demand of new and existing buildings is an objective in international energy and climate related policy initiatives. Traditionally, efforts have been focused on energy conservation measures (e.g. thermal insulation, window to wall ratio (WWR), airtightness) and modulation (e.g. shading) to reduce net demand. Highly efficient Heating, Ventilation and Air Conditioning (HVAC) units are installed to supply the remaining energy efficiently [1]. In more recent years, the integration of renewable energy is also explicitly taken into account, e.g. through the obligation to integrate renewable energy systems for deep energy retrofit and new buildings in the European Union (EU) as of 2014 [2–4]. Building Automation and Control Systems (BACS), on the other hand, have traditionally been less of a focus. Nevertheless, many sources underpin that BACS can be a cost-effective alternative or additional energy efficiency measure for the building stock [5–7]. The 2018 recast of the European Energy Performance of Buildings Directive (EPBD) recognises this, and puts explicit focus on better integration of BACS and other smart technologies in the buildings sector, amongst others through the introduction of a Smart Readiness Indicator (SRI) for buildings [8,9].

In general, BACS, also known as Building Management Systems (BMS), Building Automation Systems (BAS), Energy Management Systems (EMS) or Building Energy Management Systems (BEMS), have the intention to provide an energy-efficient, economical and safe operation of building services. The European Commission defines it, therefore, as a system that includes all products, software and engineering services for automatic controls, monitoring, optimisation, operation, human intervention and management [10–15]. In residential buildings, BACS range from a simple thermostatic valve to more sophisticated control systems like home automation systems. In non-residential buildings, BMS with programmable or dedicated functions and outstations have become commonly implemented [15]. The European standard EN 15232 classifies BACS according to seven overarching control functions [10]:

- heating control;
- Domestic Hot Water (DHW) control;
- cooling control;

- ventilation and air conditioning control;
- lighting control;
- blind control;
- technical home and building management.

The REHVA Guidebook 22 uses the same definition, but adds one more category: auxiliary energy, while other authors apply a wider interpretation: they categorise also services for life safety, alarm security, leakage detection and other smart functions under BACS [15–22].

BACS do not only improve the energy performance of buildings, they can also contribute to a more comfortable, healthy and safe environment. As the energy consumption of buildings is strongly related to the occupants consumption patterns, improved comfort might even unlock additional energy savings [23,24]. Furthermore, an automated control system provides an optimal operation of all system components and accordingly extends their lifetime. As the operation costs are reduced while the real-estate value of the building also increases, many studies show that their implementation is a profitable financial investment; BACS often results in a payback period of less than 5 years [11,15,25,26]. In addition, the implementation of BACS has the benefit of requiring less space and time in comparison to traditional energy reducing measures which is especially important in a retrofitting context, while in a professional environment, the productivity of workforce can also significantly increase [13]. Furthermore, the implementation of more advanced BACS can contribute to the connection and communication with external grids; thus enabling to harness the energy flexibility potential of the building to better match demand and supply in a smart grid context [14].

The energy performance of BACS, in specific, is described in the EN 15232 standard. This standard is part of the Energy Performance of Buildings (EPB) set of standards, which is a series of standards considering the methodology for the assessment of the energy performance of buildings within the EU [10]. EU Member States can opt for using the EN 15232 approach for representing the energy saving potential of BACS within the national energy performance certification methods, but using this approach is not enforced [27]. In this standard, technology neutral functions are defined, e.g. a function pertaining to pump control of the heating supply system. Such function can be implemented with different levels of automation, expressed as a Building Automation and Control (BAC) efficiency class. For residential and non-residential buildings four classes (A-D) are defined. Class A corresponds to high-energy performance function, whereas class D corresponds to a non-energy efficient control. By default it is assumed that existing buildings have systems that correspond to BAC efficiency class C [10].

The EN 15232 standard describes two methods to calculate the energy saving potential of BACS: a detailed calculation method (i.e. detailed energy performance analysis with case detailed information) and a factor based calculation method (i.e. BAC factor method) [10]. The BAC factor method has the advantage of being simple and relatively straightforward to implement in conjunction with energy performance certification schemes. The relative energy savings reported in this method have been derived from a limited set of building performance simulation models.

This paper sets out to review the actual achievable impact of energy performance benefits of BACS, specifically for residential buildings. Results from either measurement campaigns or more detailed parametric simulation studies will be structurally collected and compared with the EN 15232 BAC factor method, in order to assess its capability of providing sound insights on BACS performances for designers and investors.

Firstly, several easy assessment tools are discussed and their strengths and weaknesses are identified. Consequently, the main part of this paper is devoted to detailed analyses of the energy performance improvements by BACS. This paper focusses on individual BAC functionalities: heating, DHW supply, artificial lighting and shading control within residential case study buildings. Those functions are selected considering their absolute energy consumption and mutual relationship [6,28–34]. The parameters that cause the variation on the relative savings are identified, as well as some average values and intervals are proposed. To conclude, the paper compares the results of the BAC efficiency factor and the detailed energy performance analyses and identifies some shortcoming in current assessment and reporting methods. Moreover, an overview of the important parameters which influence the relative energy savings is given and advice for future research is formulated.

2 Methods

This review paper discusses simplified and more detailed assessments of BACS in residential buildings, with a focus on their energy performance. Relevant papers were collected through articles' search in databases and search engines, including Web Of Science, Science Direct, IEEE Xplore, Springer Link, MDPI and Google Scholar. In a first step, a bread database search was initiated; combining the main key words ("residential buildings", "domestic buildings", "houses", "energy performance" and "energy savings") with more specific terms per chapter (see keywords included in Figure 1). The identified records were screened on relevance, based on their title, abstract and highlights, resulting in a reduced set of records. Depending on the methodology used, these papers were further categorized into two subdivisions: (i) simplified assessment tools and their application in case studies and (ii) detailed energy performance simulations and measurements. Especially for this latter group, the collected articles were further filtered using paper- and experiment-related exclusion criteria, including:

- Topic: The scope of this paper is limited to the energy performance of BACS (i.e. heating, DHW supply, lighting and shading control) in residential buildings. Articles that not fit this scope were excluded from the selection, as well as case studies with simultaneously improvement of multiple BACS functions.
- Publication year: Due to the fast technological progress, only case studies that are published between 2014 and now (2021) were included in the review paper.
- Methodology: Only articles with a clear and detailed description of their research methodology and case study object were added to the sample.

The list of papers was iteratively expanded by also reviewing the relevance of papers cited by the selected papers, as well as papers citing the selected papers. These papers were also subject to the selection process as described above, in order to potentially include them in the final selection. Duplicate records were discarded. An overview of the included case studies and main selection criteria is given in Figure 1. The information and case studies of these papers are complemented with articles that provide additional background information.

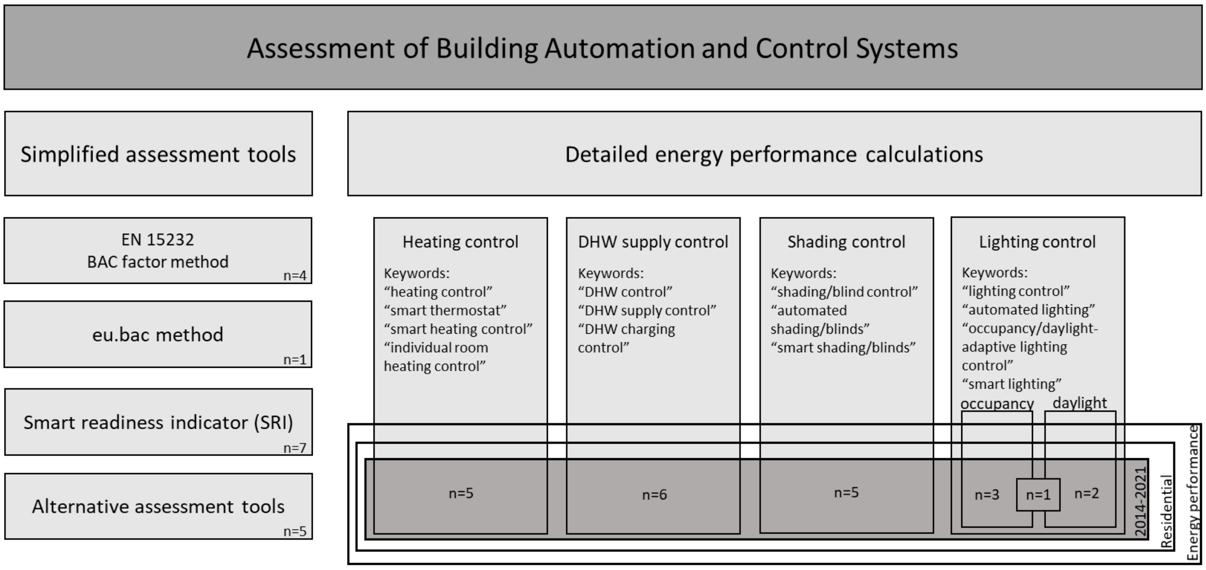

Figure 1. Overview of the collection and selection process of the included case studies (n=number of selected case studies).

For each of the selected papers, the reported energy saving potentials were collected to be mutually compared. In order to enable further processing of this data and evaluation of parameters affecting variation in reported performances, the following information was also registered:

- Type of control system and if possible, their classification according to EN 15232;
- Case study object properties, e.g. location, building type, surface area;
- Methodology: type of calculation/simulation/experiment;
- Benchmark to which the reported energy savings were compared.

Whereas the BAC factor method represents energy performance of BACS as a single figure, it is expected that building and installation characteristics can affect the achievable relative energy savings [35–37]. The energy savings of the EN 15232 BAC factor method are compared to the energy savings of comparable detailed analyses using average and extreme values. The data stemming from the review will be structured so to also provide insights on the variability of energy performance impacts and potential parameters affecting this variation.

3 The assessment of BACS performance in buildings

To report realistic energy savings of control systems, the resulting energy consumption must be assessed relative to an appropriate baseline. This baseline is strongly case depended, as there is a wide range of household comfort preferences and schedules [38]. Detailed measurements before and after BACS installations are hardly ever available in studies and would still require further processing to normalise data with regard to user behaviour and boundary conditions such as local weather conditions. Therefore, most studies rely on performance simulations rather than actual measurements. This introduces another cause of deviations, as simulation studies inevitably deploy synthetic models which are a simplification of a complex physical reality.

Evaluating the energy performance of buildings (including its BACS) is becoming more common in commercial building design and engineering practice [10,36]. Performing relevant building simulations, however, requires a significant amount of experience, time and effort, which is reflected in its cost [39]. Especially for residential buildings, the expected savings of detailed simulations for BACS will often not outweigh the cost of detailed calculations. Instead, simplified assessment methods concerning the energy performance and opportunities of BACS in (residential) buildings are proposed.

3.1 BAC factor method

The BAC factor method, as proposed in EN 15232, formulates BAC efficiency factors for seven different types of energy: two global factors concerning the thermal and electric energy and more specific, three detailed factors concerning the thermal energy for heating, cooling –only for non-residential buildings– and DHW supply and two factors with regard to the electric energy for lighting and auxiliary energy, both specific for non-residential buildings. This BAC efficiency factor expresses the energy consumption of a specific system, categorized in a BAC efficiency class, in relation to a reference scenario (BAC efficiency class C). Furthermore, those relative energy savings depend on the building type: the standard makes a distinction between residential and non-residential buildings. As a result, this method introduces no differentiation in BAC factors for various residential building typologies such as single family houses and apartment blocks. This in contrast to the method for the non-residential building sector, where EN 15232 reports distinct BAC factors for various building types such as offices, education buildings, hotels, restaurants, etc. In Table 1 an overview of the BAC efficiency factors that can be applied in residential buildings is given.

Table 1. Overview of BAC efficiency factors (f_{BAC}) for residential buildings [10].

		D	C	B	A
Overall	$f_{BAC,th}$	1.10	1.00	0.88	0.81
	$f_{BAC,el}$	1.08	1.00	0.93	0.92
Detailed	$f_{BAC,H}$	1.09	1.00	0.88	0.81
	$f_{BAC,DHW}$	1.11	1.00	0.90	0.80

Table 2. Abbreviations.

th	thermal energy
el	electric energy
H	heating energy
DHW	domestic hot water
class D	non-energy efficient BAC
class C	standard BAC
class B	advanced BAC and some specific TBM functions
class A	high-energy performance BAC and TBM functions

Ippolito et al. (2014, 2016) and Felius et al. (2020) showed that the BAC factor method is an effective and easy way to estimate the energy savings in residential and non-residential buildings when the BAC efficiency class increases [40–42]. However, the proposed methodology is limited in scope and accuracy. Bonomolo et al. (2020) proposed, for example, to expand the BAC factor approach by also introducing a BAC efficiency factor for outdoor lighting. Furthermore, they showed that related BAC savings are strongly influenced by the latitude and the corresponding time schedules [43]. In contrast, the BAC factor method neglects the influence of different climate conditions on the relative energy savings. Moreover, the standard formulates for each building type only one profile for occupancy and internal heat gains while those factors also affect the energy consumption of the building [10].

3.2 eu.bac classification system

The eu.bac system aims to inform on level of expected performance of a particular installation in a specific building through issuing certificates with a score ranging from AA to E. The classification method is based on the principles of EN 15232 as all individual functions are rated in relation to their BAC efficiency class. During an audit, all functions of this standard are examined and points are accordingly assigned. Moreover, the eu.bac system considers three additional domains: Key Performance Indicators (KPI), extended functionality and the use of certified products. All individual functions, their functionalities and domains are combined by weighting factors to achieve a global score. This global score is related to the energy performance of the building as an increase of 10 points corresponds to a reduction of the energy consumption of approximately 5%. Furthermore, the audit and certification process has to be repeated in time, with the aim to result in continuous improvements and an optimal performance of the system [11,44].

According to the eu.bac assessment, the energy performance of a university building in Odense, Denmark could reduce with 13.5% to 28.5% by upgrading the BACS from eu.bac method category E to a class C and class AA system, respectively. However, this methodology provides only an estimation of the energy performance of the system as all European regions are covered by a global climate zone. Next to the building type, this parameter affects, in reality, the relative energy distribution between the investigated domains [25].

3.3 Smart Readiness Indicator (SRI)

In the 2018 revision of the EPBD a new common EU assessment scheme for smart buildings was introduced: the smart readiness indicator (SRI) [8]. The SRI aims to assess the ability of a building (i) to adapt to the needs of the users, (ii) to facilitate maintenance and efficient operation and (iii) to adjust to the situation of the energy grid. The SRI is developed to raise awareness on the benefits of smart controls in buildings in order to stimulate the investments and implementation of BACS by building owners and to support technical innovation in the building industry [12].

Technical support studies have further developed the methodology of this indicator and suggested and evaluated potential implementation pathways [12]. In October 2020, a Commission Delegated Regulation and Commission Implementing Regulation were adopted, officially introducing the SRI as a common Union scheme [45,46]. The methodological framework of the SRI is a multi-criteria assessment scheme, evaluating the potential for smart services in a building. The score is normalised, compared to the maximum impacts that could be achieved in a particular building. In the evaluation nine technical domains and seven impact criteria are evaluated. Within a domain, each functionality has various levels of smartness and two to five corresponding functionality levels are formulated. During an audit all available services in the building are reviewed and accordingly, weighting factors are applied to combine all services into a global parameter. Those weighting factors are case specific as they are related to the building type and climate zone. Two type of audits are proposed: a simplified method where 27 services are considered and a detailed method, taking 54 services into account. As the simplified method only evaluates half of the functionalities, the procedure is mainly applied for residential buildings, while the smart readiness of non-residential buildings is preferably evaluated by the detailed method [12].

During the development process of the SRI by the technical support studies, stakeholders were given the opportunity to test the methodology and provide feedback to the study team. Various authors have reported their experiences with the draft methodology. They concluded that for all investigated building types, the proposed indicator provides clear and understandable information about its smartness [47]. They also perceive a need for detailed assessment protocols to increase the replicability of the assessment, and point towards the dependency of available information for legacy systems [48–50]. Some authors suggest to extent the SRI with more quantitative data, e.g. proposing to quantify the load shifting potential of smart buildings and their interaction with the energy grid [51]. In such case, it is not solely the potential (or readiness) that is assessed, but also the actual in-use performance, e.g. based on the evaluation of an extended period of monitoring data.

3.4 Alternative assessment tools

Next to the aforementioned assessment methods, various researchers have proposed their own indicators to provide insights on the smartness of buildings and the corresponding energy performance. Within the BuildCOM project, the IBACSA tool is developed. This rating is based on the principles of EN 15232 and consists of a qualitative and quantitative assessment, where 60 services are evaluated for five criteria, i.e. energy efficiency and flexibility, maintenance and fault prediction, comfort and provided information to the occupants. The result allows to compare and to select the most appropriate BACS alternative for a specific building during the design stage [52]. Furthermore, the Smart Buildings Alliance (SBA) has created more advanced certification labels for smart buildings (i.e. ready2services and ready2grids) that are commercially available [53,54]. The more traditional building rating and certification systems, like LEED and BREEAM, do not explicitly account for BACS. Some other sustainability assessment tools like DGNB recently added an additional criterium with respect to advanced building technologies [11,55–57]. However, none of them is intended to estimate the energy savings that can be achieved by the implementation of BACS.

In conclusion, various simplified assessment schemes for BACS performance in buildings exists including BAC factor method, eu.bac classification and the SRI. The main purpose of those assessment tools is to compare various building design based on smartness and energy consumption. The methods require minimal input and their results are presented so that they are easy comprehensible for a non-technical audience. These approaches are mainly based on a checkbox approach, and due to the simplified nature of these assessment methods do not or only very limitedly quantify the BACS impacts.

4 Evidence of BACS energy saving potential

This chapter reviews scientific literature with respect to detailed performance analysis of BACS in residential buildings. The analysis is focussed on four main functions of BACS systems in domestic buildings, namely (i) heating control, (ii) domestic hot water control, (iii) lighting control and (iv) shading control.

4.1 Heating control

Heating demand in buildings is governed by many parameters, related to outdoor environmental conditions, building characteristics, heating systems setup, user behaviour and control features. Table 3 lists a selection of studies which focus specifically on the impact of automation and control on the space heating energy consumption in domestic buildings.

Rodríguez-Pertuz et al. (2020) reported that 7% to 95% of the heating energy could be saved due to zoned-control compared to central heating control. The broad variation within the reported relative savings can be attributed to the various scenarios that are simulated for this study. They investigated the influence of the apartment size, characteristics of the building envelope, different climate zones, occupancy patterns with corresponding heating schedules and door opening percentages (i.e. rate of air exchange) on the energy savings that are realised by improving central heating control. Of those, the amount of air exchange is reported to have the most significant influence on the relative energy saving potential of individual heating control with differences until 19% between the simulated variations [58]. Nevertheless, only the two extreme door opening situations (i.e. always open and always closed) are simulated, while in realistic situations the position of the door varies through the day. Cockroft et al. (2017), furthermore, have investigated four variations of this specific parameter and it can be concluded that the achievable relative energy savings of individual room heating control compared to central heating control are strongly correlated to the amount of air exchange between the rooms [59]. Moreover, both studies concluded that the relative energy saving increases for smaller families and lower occupancy rates [58,59]. In contrast, the influence of the heat resistance of the building envelope only has a minor effect on the relative magnitude of savings from automated control. More specific, improving the heat resistance of the building envelope results in lower relative energy savings. This impact is found to be more pronounced for a detached building (bungalow) than for a semi-detached building. In general, this study reported a reduction of 8% to 37% after the implementation of individual room control in comparison to traditional central heating control [59]. Next to simulations, a measurement campaign of 8 weeks was conducted in a semi-detached house. Extrapolating the data resulted in a predicted relative annual energy reduction of the same order, i.e. 12%-13%, with small variations due to different climate data, while the experienced indoor comfort remains the same. Hereby, the energy consumption of a pair of comparable semi-detached buildings with similar synthetic occupant behaviour are compared. The introduced occupant behaviour neglects the occupant-building interactions and as a consequence higher energy savings could be expected when those actions are included [60].

The impact of various heating control strategies on the realised energy savings and comfort level is explored as well. The energy consumption of an occupancy driven smart thermometer with fixed setpoint can reduce the energy consumption by 11% to 34% compared to continuous heating, whereas an adaptive occupancy driven control even lowers the energy demand with 20% to 64%. However, the relative savings depend on the climate zone: both algorithms have a higher potential in hot climates than in cold regions [61]. The effect of thermostat control is also explored by Kull et al. (2020). Based on simplified simulations, they showed that smart thermostats have the highest relative saving potential when a lower setpoint is selected in cold climates: a reduction of 8% is found when the temperature setpoint is 21°C, while only 6% energy is saved when a temperature of 23°C was targeted, in comparison to a fixed temperature setpoint of 21°C and 23°C respectively. Additionally, the concluded that also the presence of a ventilation system with heat recovery causes an increase of 1% to 4% in the relative energy saving that are attributed to the smart thermostat. In general, energy savings of 5-11% are reported when the temperature setpoint is scheduled room specific. Nevertheless, there is significant variation between the rooms and more specific, a linear correlation (R^2=0.9674 and R^2=0.9471, respectively without and with ventilation) can be found between the relative energy savings and the time at lowest setpoint [62]. Kleiminger et al. (2014) found a similar relation as they concluded that the performance of predicting occupancy control systems is linearly correlated to the occupancy rate for poorly insulated buildings, while this relationship is less pronounced for buildings with an improved heat resistance of the building envelope. This resulted in reduced efficiency gains for colder and cloudier climate zones. Thus, the realised energy savings are also here subject to the building structure, occupancy schedules and climate conditions, resulting in an interval between 6% and 17% for the relative energy savings. Contrary, within the predicting occupancy control systems, the applied algorithm appears to not significantly affect the efficiency gain [63].

All papers and control systems presented discuss the upgrade of emission heating control system from a traditional central heating system (EN 15232 BAC class D) to a central smart thermostat (class D) or an individual room control with communication (class A). Although all kind of central heating control systems are categorized in class D in accordance to EN 15232, energy savings up to 25% of the yearly heating energy are reported when an intelligent thermostat is installed. Similarly, the applied occupancy control algorithm can affect the energy consumption. In general, the standard only distinct three classes (class B does not exist for domestic heating emission control), grouping various control systems within the same class although they affect the energy performance differently. The achieved energy savings can even further increase when individual room control is implemented, with reported values ranging between 5% and 95% in the discussed case studies. This spread can be attributed to different building and installation properties, for example air exchange rates, building type and thermal resistance of the building envelop, and various boundary conditions and usage patterns. Those parameters mutually influence each other so that it is impossible to characterize the impact of a sole parameter in all situations. Two of those parameters (i.e. air exchange and occupant presence) are simplified in the discussed case studies. In the reviewed papers, the occupant behaviour is presented as a returning deterministic model and consequently, an occupancy-based thermostat can easily predict the preheating time. However, realistic presence models include unexpected attendance. The comfort is, therefore, reduced as warm-up time is required to match the predefined setpoint. Furthermore, human-system interactions are not included in any of the discussed studies. Occupants can override the settings, but override behaviour does not significantly affect the energy savings as they have a short duration or are frequently adjusted [64].

In the reviewed literature, both simulation based studies and measurement campaigns yielded similar results [59,60]. Nevertheless, all proposed models are a simplification of the intricate nature of the build environment.

Table 3. Overview of residential case studies with respect to heating control.

study	location	methodology	building	control mechanism conform EN 15232 (reference)	energy savings
Rodríguez-Pertuz et al. (2020) [58]	Almeria, Bilbao and Burgos Spain	simulations in EnergyPlus	apartments of 52 m² and 103 m²	emission control A (central heating control)	7%-95% of the annual heating energy
Cockroft et al. (2017) [59]	London and Glasgow United Kingdom	simulations in ESP-r	semi-detached house and detached bungalow	emission control A (central heating control)	8%-37% of the annual total energy
Beizaee et al. (2015) [60]	Loughborough United Kingdom	measurements during 8 weeks and extrapolation	semi-detached house of 91.2 m²	emission control A (traditional control)	12%-13% of the annual heating energy
Wang et al. (2020) [61]	Fairbanks, New York City, San Francisco, Miami and Phoenix USA	simulations in EnergyPlus	house of 223 m²	emission control D (fixed setpoint)	25% of the annual total energy
Kull et al. (2020) [62]	Tallinn Estonia	simulations in IDA ICE	house of 100 m²	emission control A (constant heating setpoint)	5-11% of the annual energy
Kleiminger et al. (2014) [63]	Lausanne Switzerland	simulations	studio flat of 52 m² and house of 176 m²	emission control D (fixed setpoint)	6% to 17% of the annual energy

4.2 Domestic hot water supply control

Domestic hot water supply represented 16% of the energy consumption for an European residential building in 2012, but can amount up to 50% of the energy demand of an energy-efficient dwelling and therefore its relative share is expected to increase the next years [65,66]. Improving the control of a DHW supply could result in significant energy savings.

By introducing a simple scheduled control for a horizontal-oriented electric water heater, 29% of the input energy can be saved compared to temperature control, reducing the effective usage and standing losses [67]. However, the temperature and energy were not matched with the reference scenario, overestimating the achievable energy savings. In a second laboratory experiment with extended heating periods, matching the outlet temperature of the heater for both scenarios corresponded to a reduction of the relative energy savings with 10% (i.e. 16% to 6%) [68]. Both studies reported a mismatch between the results of various assessment methods: the results of the simulations underestimated the standing losses in comparison with the lab and field measurements [67,68]. Moreover, Booysen et al. (2019) investigated the performance of three different control systems: (i) the temperature-matched scheduled control is defined as the optimal control of the heating element switching sequence, thus minimizing the thermal losses while ensuring that water is drawn at the same temperature and volume, (ii) the energy-matched schedule control lowers the target temperature when water is drawn, while the volume of tapped water increases to deliver the same amount of energy and (iii) the energy-matched schedule control with daily Legionella sterilisation adds a daily increase of the water temperature to 60°C during 11 minutes to the energy-matched scheduled control. The temperature-matching method was found to save about 8% of the energy consumed by a classic thermostat control, while the energy-matching control even reduces the energy demand with 18%. This latter methodology combined with Legionella sterilisation still lowers the energy consumption by 13%, whereas it significantly reduces the risk of Legionella infections. For the energy-matched control strategies, the standing losses have almost been halved. Furthermore, they investigated 30 different heaters, which resulted in a range of energy savings for each control and only median values are here reported. In general, the installation and applied control algorithm have a significant influence on the achieved energy savings [69]. In a next paper, this model was further refined to include stratification (i.e. two-node model) and probabilistic water use patterns for a vertical electric hot water heater [70]. In general, this results in lower energy savings: the median electrical energy reduction of 77 electrical water heaters was only 2% for the temperature-matched optimization and 10% for both energy-matched schedules. More extreme cases of 34% savings are reported as well, depending on the investigated water heater and water usage pattern. The use of unpredictable hot water draw schedules leads to a decrease of the potential up to 56% compared to perfect foreknowledge [71]. The same conclusion is reported by Sonnekalb et al. (2019) as they propose a DHW storage charging control that predicts automatically the individual human behaviour with neural networks and Gaussian Process models. This kind of predictive control results in energy savings between 19% and 34% when they are compared to a default schedule. This variation is caused through errors in the prediction models and is closely linked to the predictability of the user behaviour. As a result of the prediction models, the discomfort, moreover, increases since the waiting period increases when hot water is demanded between the operating times [72]. This impact of the water draw profiles is also recognised by Kepplinger et al. (2015). They reported energy savings of 11%-12% for an energy-driven optimization, compared to night-tariff switched DHW heater with only small difference caused by variances within the user scenarios (i.e. variation in maximal water temperatures and draw-off volumes) [73].

In conclusion, the performances of traditional charging control systems of classes A and C, in compliance with EN 15232, are discussed and an overview of all investigated papers is given in Table 4. Since the respective authors have each formulated their own baseline scenario to compare the improved controls to, their findings are not directly comparable by the lack of a common reference. Moreover, they are expressed in different energy types and they refer to different time periods. Reducing the total heating loss corresponds to a smaller decrease of the total electric energy and there is no (linear) correlation between annual and daily energy savings. Furthermore, a mismatch between various assessment methods is reported and can be attributed to simplifications (e.g. stratification is neglected or simplified, perfect foreknowledge of the water usage schedules) in energy performance simulations. Higher relative energy savings are, therefore, reported in comparison to field measurements.

Further differentiation in the energy performances of BACS can be attributed to the heater properties, hot water draw patterns and heating settings [74]. Next to this, the applied control algorithm affects the energy performance as various control algorithms within one BAC efficiency class lead to different results. Moreover, the inlet and outlet water temperature will probably affect the performances of advanced DHW supply control as well, but information about this is not mentioned in any of the studies. In contrast, the DHW supply control is not sensitive to building design features and other contextual factors, such as the climate zone and consequently, their performances are not evaluated within specific case study buildings. In general, introducing predicting schedules and control systems decreases the DHW heating energy in all reviewed studies, however at the risk of decreasing comfort and increasing Legionella contamination risks.

Table 4. Overview of residential case studies with respect to DHW supply control.

study	location	methodology	building	control mechanism conform EN 15232 (reference)	energy savings
Booysen et al. (2019) [69]	-	simulations	-	control of DHW storage charging with direct electric heating or integrated electric heat pump A (continuous charging)	4%-26% of daily the domestic electric energy
Booysen et al. (2016) Cloete et al. (2017) [67,68]	-	lab and field experiments and simulations	-	control of DHW storage charging with direct electric heating or integrated electric heat pump C (temperature control)	up to 29% of the daily input energy
Ritchie et al. (2021) [71]	-	simulations	-	control of DHW storage charging with direct electric heating or integrated electric heat pump A (traditional thermostat control)	1.3%-34% of the daily electric energy
Sonnekalb et al. (2019) [72]	-	simulations and calculations during winter months	-	control of DHW storage charging with direct electric heating or integrated electric heat pump A (default schedule)	19%-34% of the daily heating energy
Kepplinger et al. (2015) [73]	-	simulations in MATLAB	-	control of DHW storage charging with direct electric heating or integrated electric heat pump A (night-tariff switched)	11%-12% of the annual heating energy

4.3 Lighting control

As stated by Simpson (2003), office buildings are the most important application of automated lighting control systems, and thus, their performances are mostly investigated in such an environment [75–77]. Fewer researchers also examined their impact in residential buildings. The investigated automated lighting systems can be divided in occupancy-based and daylight-linked control systems.

Occupancy-based control systems have the highest saving potential as they are implemented in irregular occupied rooms [78,79]. In residential buildings, a stairwell (of an apartment building) fits the requirements to achieve high energy efficiency due to the installation of motion sensors as it has an infrequent and unpredictable occupancy pattern. Lighting energy savings up to 98%, compared to a situation with continuous lighting modus, are reported in an apartment building in Ukraine [80]. This is probably a significant overestimation of the reality as manual lighting will probably not be switched on continuously, especially with eco-conscious residents. Lee et al. (2017) and Soheilian et al. (2019) investigated the performance of an occupancy-based control strategy in an apartment. A relative energy saving of 12% of the total lighting energy is reported in comparison with a manual on/off control. For this manual control, it is assumed that the residents do not turn off the lights as they return within about 15 minutes to the room. Limitations to this study are that it only covers a time span of three days and that the presence of daylight is ignored [81]. Soheilian et al. (2019) started their performance analysis with the same assumption. This resulted in energy savings of 27% and 34% for the kitchen, living room and bedroom, depending on the defined occupancy patterns. In this respect, the energy reduction increases as the occupancy becomes more irregular or increases [82]. Nevertheless, the potential of smart lighting systems is overestimated as dimming in only included for the occupancy-based lighting control and illumination by daylight is neglected. Furthermore, it is not clear of the energy use of sensors is included in the calculations: the automated lighting is scheduled based on the perfect foreknowledge of the occupant behaviour.

More realistic simulations can be performed by implementing the daylight presence and adjust the light control accordingly. Dimming daylight-linked control systems are often combined with occupancy sensors to realise more optimal lighting control. In simulations, the combination of occupancy and daylight-driven lighting systems resulted in a reduction of the electric lighting energy with approximately 10% without delay. Only small differences between a single-, two- and three-person household are reported. In contrast, the delay time has a major impact on the energy consumption of automated lighting applications, increasing the energy consumption with 6%-10% to 19%-30% for a 5 minutes and 15 minutes delay respectively. As a consequence, the initial energy savings of the advanced control systems are here neutralized when the delay exceeds 5 to 8 minutes [83]. Nevertheless, the setting of such a delay is a trade-off between achievable energy savings and the comfort perception of the residents [84]. Higher energy savings are probably achievable as it was assumed that building residents immediately turn on and off the lights when the illuminance level exceeds a predefined limit value [83].

The impact of dimming control is also separately evaluated by some authors. Bonomolo et al. (2017) evaluated the lighting electricity consumption and lighting parameters for ten summer days in Italy. The implementation of a daylight-linked control system resulted in daily lighting energy savings between 0% and 36%, with an average of 20% in relation to a reference scenario with simulated on/off control. They assumed that the lights have equal operation hours for the automated and on/off control, but the lights cannot be dimmed in case of the on/off control. The differences between the energy savings can be explained by variations in daylight conditions and different schedules, although no correlation can be found between the reported occupancy patterns and relative energy savings [85]. Furthermore, Beccali et al. (2017) & Bonomolo et al. (2021) examined the performances of control systems of BAC efficiency class C, i.e. a manual on/off control per room, and an automatic dimming light of class A, in accordance to EN 15232, at the same location. The results of a 13 month measurement campaign were extrapolated in order to obtain annual results: only 4%-17% (average of 9%) of the lighting energy was saved over a central manual on/off control when a system of class C was implemented, whereas those savings increase to 19%-25% (average of 22%) when the system is upgraded to BAC efficiency class A. The differences between the energy savings can be here attributed to various daylight conditions (i.e. seasonal variations in daylight illuminance), applied control system and sensor position and light efficiency. Less energy efficient energy sources only resulted in an increase of about 1% of the relative energy savings, while differences up to 5% were noticed for different sensor locations and control systems. Those difference are also noticed for a class C systems, which the standard EN 15232 describes as manual control per room. In normal circumstances, there are hereby no sensors or advanced control algorithms. Furthermore, the baseline scenario, a manual control system of class D, is not further specified as well and consequently, those values have a low reliability [86,87].

In all reviewed cases (Table 5), the implementation of automated lighting control resulted in a reduction of the lighting energy consumption compared with traditional manual control. The potential to decrease the lighting energy consumption with occupancy or daylight-dimming control systems is of the same order, while combining both will lead to the lowest energy savings. It must be noted that the results are here combined to a more realistic baseline scenario. The methodology that was followed to estimate those energy savings is in all cases a simplification of the complex reality: for instance, the impact of occupancy-driven lighting was researched neglecting the daylight illuminance, manual control was simplified and measurement campaigns were only performed for limited time spans. Furthermore, only lighting energy is here considered, while lighting produces additional internal heat gains. This affects also the thermal, i.e. heating and cooling, energy performances, while those performances are here not evaluated [6,88,89]. Especially for the occupancy-driven control systems, the made assumptions resulted in a major overestimation of the achievable energy savings. In general, this additional energy waste of manual control is a result of human imperfections as they forget to turn off the light when leaving. As a consequence, the amount of unnecessary activated hours in the reference scenario also influences the gained profit. Next to the human control behaviour, the presence of the residents affects the results as higher occupancy rates (especially average and peak occupancy rates) and irregular patterns increase the potential of smart lighting [79,90]. Moreover, the energy reduction is also sensitive to control-related properties like the applied control algorithm, sensor location, time of delay. In this regard, a shorter time delay for switch-off reduces the energy consumption of occupancy-driven control. However, the minimal time delay is defined to be 7 minutes in order to achieve an acceptable lighting comfort [75,78]. As this time delay was set in the case study by Hafezparast Moadab et al. (2021), the combined occupancy- and daylight-driven control system will no longer positively affect the lighting energy demand [83]. It can be expected that also other boundary conditions have their impact, although those are not investigated in the discussed studies [90–92].

Table 5. Overview of residential case studies with respect to lighting control.

study	location	methodology	building	control mechanism conform EN 15232 (reference)	energy savings
Burmaka et al. (2020) [80]	Ternopil Ukraine	observations of the lighting pattern during 4 weeks and calculations	stairwell of apartment building	occupancy control A (continuous lighting mode)	94%-98% of the lighting energy
Lee et al. (2017) [81]	-	measurements during 3 days	apartment (residential model)	occupancy control A (manual control)	12% of the daily lighting energy
Soheilian et al. (2019) [82]	Sweden	calculations in excel	one bedroom apartment	occupancy control A (manual control)	27%-34% of the annual lighting energy
Hafezparast Moadab et al. (2021) [83]	Gothenburg Sweden	simulations in DIALux	two-room apartment of 75 m²	occupancy control A light level/daylight control A (manual control)	-10%-10% of the annual electric lighting energy
Bonomolo et al. (2017) [85,93]	Palmero Italy	measurements during 10 days	laboratory of 106 m² (apartment: residential model)	light level/daylight control A (manual (on/off) control)	0%-36% of the daily electric lighting energy
Beccali et al. (2017) Bonomolo (2021) [86,87,93]	Palmero Italy	measurements during 13 months	laboratory of 106 m² (apartment: residential model)	light level/daylight control C and A (manual control)	4%-17% and 19%-25%, respectively, of the annual lighting energy

4.4 Shading control

Another type of building automation and control systems with an important relevance to domestic buildings is the control of shading devices. The EN 15232 standard takes a narrow view on this topic, only treating blind controls. In this review, the scope is broadened to also include other types of shading systems. Most of the research on the topic of shadings and their control is focussed on non-residential buildings, and in particular office buildings, because the higher internal gains and the direct impact of thermal comfort on productivity of the employees [94–102]. Nevertheless, the implementation of shading in residential buildings can also improve the thermal indoor and visual comfort and lower the thermal energy consumption.

Several papers, see Table 6, investigated the effect of different control strategies on the energy performance of a residential model. The first study showed that venetian blinds with an automated control strategy reduce the annual energy consumption with 15% compared to fixed shading with an inclination angle of 80°. More specifically, the savings incline to 30% till 60% in summer, whereas the energy demand in winter decreases with 10% till 20% through additional solar gains. Those energy savings are achieved for a simplified one-room model of only 25 m² with one window in each orientation. Furthermore, the lighting is assumed to be switched on as the residents are present and awake, not profiting of daylight illuminance. Through this assumption, the position of the blinds have no impact on the lighting energy consumption [103]. Yao et al. (2016) simulated the energy performance of four automated control strategies and concluded that relative heating and cooling energy reductions with 5% to 11% are possible, only by changing the applied algorithm and corresponding sensor: solar radiation driven control reduces the energy consumption more than systems that react on indoor temperature sensors, combined solar radiation and indoor temperature sensors and outdoor temperature sensors. However, the orientation of the windows has an impact on the ranking of those control strategies. Furthermore, it must be noticed that only heating and cooling energy are included in the comparison; thus excluding effects on artificial lighting energy use [104]. San Martin et al. (2017) also recognized that a simplified solar radiation-based control system achieves equal energy savings as more complex control systems, expanding the analysis by including the influence of the type of blinds and the window properties. They found that four of the five investigated control strategies resulted in a reduction of the energy consumption, ranging from 15% till 35% compared to a scenario where the blinds are only closed during night. Taking into account the competing interests (i.e. energy consumption and natural illuminance), the thermal energy consumption increases again with 2%-5% for half open blinds compared with the thermal energy optimization with closed blinds. However, this study only takes into account heating, cooling and dehumidification energy, while shading also influences the consumed lighting energy [97,98]. Furthermore, the energy reduction is related to the thermal characteristics of the windows since the relative energy savings realised with automated control strategies by triple glazed windows are approximately 10% smaller compared to the savings realised by double glazing windows. Moreover, two types of shutters, i.e. massive and non-massive, are investigated, resulting in an additional decrease of the thermal energy by about 12% when double glazed windows are installed, while this difference is almost neglectable when high efficient triple glazing is applied [105]. Moreover, Firląg et al. (2015) found savings between 8% and 20%, with an average of 13%, of the total energy consumption when automated control is installed compared to manual control. The energy consumption that corresponds to the manual control is calculated based on a survey that identified the state of the blinds during the day. Hereby, the manual control is simplified to three different states and only three periods during day and two seasons were distinguished. The human behaviour is really simplified as responders only could choose one option for a whole season [106]. Furthermore, the variance in relative energy savings is attributed to different control algorithms and climatic conditions. In this respect, automatic shading has more potential in cooling dominated climates as they mainly affect the consumed cooling energy [107].

In conclusion, by introducing automated control algorithms, the annual energy consumption is reduced with 8%-35% compared to conventional manual control. However, it is important to notice that the reviewed studies not all refer to the total energy consumption. Firstly, this broad range can be explained in relation to the various reference scenarios: Yao et al. (2016) only investigated control strategies which are classified in BAC efficiency class B, whereas there is also referred to manual control and operation, respectively, classes C and D. The lowest energy reduction is expected when is compared to the most performant baseline scenario, while other factors (e.g. building characteristics and location) also affect the achieved energy savings. The intricacy of comparing results of BACS savings reported by authors using different methods and benchmarks is also apparent here: while San Martin et al. (2017) report 26% energy savings when improving from BAC efficiency class C to B; the savings reported by Firląg et al. (2015) are lower (13%) although here the class B performance is compared to manually operated shading (class D). Nevertheless, the differences between manual operation and control are almost neglectable in a simulation as both make an assumption that the occupants not actively react on solar radiation and overheating. Furthermore, the different studies also indicate that the highest energy reductions are achieved for well-insulated massive buildings with a high WWR. Next to the building characteristics, the realised profit also depends on the investigated control algorithm and shading type.

Table 6. Overview of residential case studies with respect to shading control.

study	location	methodology	building	control mechanism conform EN 15232 (reference)	energy savings
Nicoletti et al. (2020) [103]	Cosenza Italy	simulations in EnergyPlus	square room of 25 m² (residential model)	blind control B (fixed shading)	15% of the annual heating, cooling and lighting energy
Yao et al. (2016) [104]	China	simulations in EnergyPlus	apartment building of 3168.9 m²	blind control B (outdoor temperature sensor)	5%-11% of annual the heating and cooling energy
San Martin et al. (2017) [105]	Madrid Spain	simulations in TRNSYS	residenatial building of 67 m²	blind control B (closed during the night and open when there is radiation)	15%-35% of the annual heating, cooling, humidification and dehumidification energy
Firląg et al. (2015) [107]	Anlanta, Phoenix, Minneapolis and Washington DC USA	simulations in EnergyPlus	residential building of 223 m²	blind control B (manual operation)	8%-20% of the annual total energy

5 Discussion

The results of more detailed energy performance assessments are compared to the simplified procedures of EN 15232, i.e. the BAC factor method. This factor method is the underlying evaluation method of the eu.bac certification system and the SRI.

The methods to assess the impacts of the implementation or upgrade of BACS in residential building can mainly be divided into three groups. First of all, (i) simplified energy performance assessments allow to estimate the energy savings without any difficult computation. In this regard, the BAC factor method provides guide values that may be applied for all types of residential buildings. The selection of the appropriate BAC factor is only subject to the level of automation (i.e. different BAC efficiency classes) and the energy type. Moreover, this standard is often implemented in complete ratings and certification tools who judge the energy performance and the potential of implementing BACS within a building. The results of those assessment tools are expressed as a number or classification and therefore, comprehensible without any foreknowledge. They are thus helpful to illustrate the potential for a non-technical audience, and instigate them to further upgrade the BACS.

Next to simplified methods, the relative energy savings can be determined by (ii) measurements. Those measurement campaigns are often limited in time and, only daily or monthly results are accordingly obtained. In order to achieve annual information, extrapolation is applied, but this adds a secondary uncertainty to the results. Moreover, there are differences reported between the measurements of the reference case and improved situation as both are integrated in various buildings or are tested at different moments, for example. Hereby, the human behaviour is a parameter that is out of control for the researchers. Fictive internal heat gains could be included in measurement campaigns as workaround, but this implies simplifications in human-building and human-system interactions.

A third assessment method to predict savings attributed to BACS is by making use of (iii) detailed numerical energy performance simulations. Such an assessment results in detailed time-series data and annual information about the energy performance. Simulations allow parameter analysis thereby supporting decision making in the design process. Nevertheless, in order to perform such a dynamic simulation with sufficient detail, a significant amount of experience and effort is required. In general, it is difficult to include the unpredictability of the human behaviour and as a consequence, the results of simulations do not fully coincide with the achieved savings. Accordingly, there could be a mismatch between the results of the simulations in comparison to the results that are found with measurement campaigns. Especially for DHW supply control, this is reported and can be attributed to simplifications in the simulation model and perfect foreknowledge of the occupant behaviour

Table 7. Overview of the average energy savings.

	BAC efficiency class		energy savings				difference
	reference	improved	BAC factor	detailed analyses			
				minimum	maximum	average	
emission control heating	D	A	26%	5%	95%	20%	-6%
occupancy control lighting	C	A	8%	12%	34%	24%	+16%
shading control	D/C	B	14/7%	8%	35%	17%	+3/10%

Table 7 provides an overview of three discussed BACS improvements and their energy performance, according to the BAC factor method and an average value for the savings reported in more detailed analysis in scientific literature. The BACS that are investigated in the detailed case studies are assigned BAC efficiency classes and subsequently, average annual energy savings for all functionalities are calculated. This average is not an absolute value since results of various studies are compared and consequently the sampling is not proportional. Besides this, the interval of the reported energy savings is given as well to give an idea of the spread on those results. Furthermore, it is here impossible to report one single value for DHW storage charging control since the various case studies refer to different baseline scenarios and both, annual and daily energy savings are reported, while only annual results can be compared with the BAC efficiency factor.

The results show that there are small to moderate differences between the average energy savings of the detailed studies and the corresponding BAC efficiency factors. For the case studies investigated, the BAC factor for heating energy is an overestimation of the energy savings for emission control by heating with 6%, but the variation on those results is considerable. On the other hand, the BAC factor for electric energy underestimate the energy savings that can be achieved by upgrading the BACS to occupancy controlled lighting with 16%. The energy savings that are reported here all exceed the prediction of the BAC factor. Furthermore, the same BAC factor corresponds to the average energy savings that are achieved when shading control is upgraded from class D to B in detailed computations and here a small underestimation of 3% is reported. Manual operation and control were here combined as the underlying control algorithm is almost the same for both. When those results are consequently compared with BAC efficiency class C (manual control) the BAC factor underestimate the results with 10%.

In general, the BAC factor can be used as rough first estimation, although those energy savings can show substantial deviations with more realistic case studies. This is caused, inter alia, by differences within the considered energy types. EN 15232 propose separate BAC efficiency factors for thermal and electric energy types, while the relative energy savings that are reported in the more detailed case studies refer to a combination of energy types. The BAC factor for electric energy is, for instance, applied for blind control, whereas a significant part of the energy savings are related to heating and cooling energy. Moreover, interpretation is required to categorize BACS in the various BAC efficiency classes and when an inaccurate class is selected, a wrong BAC factor is applied. Lastly, the building properties and contextual factors that are considered have an influence on the calculated results.

Originally, the BAC efficiency factor was based on the analysis of a 'shoe-box model', which is not a realistic building model, while only one occupancy pattern is taken into account and the influence of the climate zone is neglected [10].

Table 8. Overview of the factors affecting the relative energy savings.

parameter	heating	DHW supply	lighting	shading
building design				
building/room type	X		X	
building/room dimensions	X		X	
characteristics of the building envelope	X		X	X
amount of air exchange between rooms	X			
installation design				
type of installation		X	X	X
design properties of the installation		X	X	
settings	X	X	X	
control algorithm	X	X		X
contextual factors				
occupant behaviour	X	X	X	
climate zone	X	X[1]		X
latitude and orientation	X	X[1]	X	X

In reality, the achieved energy savings are subject to different building characteristics and boundary conditions. An overview of the identified parameters for each control system is given in Table 8. This overview is probably not comprehensive as only a limited number of parameters are yet investigated for each function in scientific literature. All mentioned parameters could be divided in three categories. Firstly, the building design features influence the energy performances of heating, lighting and shading control systems. Moreover, the two remaining groups of parameters, the installation properties and contextual factors, affect the relative energy savings of the four investigated functionalities. In general, it can be concluded that higher relative energy savings are achieved when the absolute energy consumption of the related energy types is increased, although the influence of the occupancy rates on all control systems is not that clear. Furthermore, the implementation of more advanced control systems results in the highest relative energy savings in moderate and hot climate zones, whereas the highest absolute savings of advanced heating control are achieved in colder places. The geological location, and more specific the latitude, affects the performances of all investigated control systems. Especially for lighting, daylight conditions strongly impacts the potential of automated control, while the sun irradiance affects the operation of renewable energy sources and produces internal heat gains.

Since the relative energy savings are influenced by case-dependent parameters, they have to be calculated for an appropriate scenario in order to achieve realistic results. Realistic occupant behaviour and human-building interactions seems difficult to implement correctly in simulations and measurement campaigns. As they can affect the achieved energy savings, those simplifications affect the retrieved savings, often reducing the extreme values.

Moreover, since the various authors did not use a common approach to define the baseline scenario, results obtained for different case study buildings are very difficult to compare. Moreover, only part

[1] Only for renewable energy devices [108]

of the reviewed papers contains detailed information, e.g. characteristics of the building, occupancy patterns, etc., about their case study, while this information is required to interpret the reported energy performances and also an prerequisite to repeat some of the analyses by other authors.

6 Conclusion

There are various assessment methods available for BACS nowadays. Simplified assessments as the BAC factor method of EN 15232, SRI and the eu.bac method give insights in BACS performances for a non-expert audience and can encourage the uptake of advanced systems. This work set out to review the achievable energy performance savings as reported in measurement campaigns or more detailed simulation studies, and compare this to the relative energy savings as defined in the BAC efficiency factor method of EN 15232, with a focus on residential applications. The analysis shows that the energy performances of BACS reported in more detailed calculations deviate by 6% to 16% from the relative energy savings obtained with the simplified BAC factor method. An interval of energy reductions is reported for each of the improvements as the relative energy savings are sensitive to three groups of boundary conditions: building design features, installation characteristics and contextual parameters. The performances of heating, lighting and shading control are affected by the three categories, while only the installation design and context influence the performance of DHW supply control. The impact of each investigated parameter can be investigated in dynamic building energy performance simulations. Nevertheless, those results can also slightly differ from the reality as simplifications and assumptions are included in the evaluation. Often, the occupant behaviour is modelled in a highly simplified way, e.g. through the use of deterministic schedules. In reality, user behaviour is much less predictable; leading to less optimal control in actual operation conditions, which results in lower comfort and higher absolute energy consumption.

This study explored some of the potential factors affecting the relative energy savings, but more work is to be done in order to complete this list and to clarify and quantify their relation with the energy performance. It appeared that the formulation of realistic and unpredictable occupant behaviour is crucial to estimate those energy savings. Additional parameters as thermal and visual comfort should be included as well to improve the human comfort perception and energy performance simultaneously.

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