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Review article

# Challenges and opportunities in European smart buildings energy management: A critical review

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## ABSTRACT

The substantial stock of European buildings, accounting for more than 40% of energy consumption, has prompted member states to establish a renovation standard with stringent performance criteria. As advancing into the era of digital transformation, the concept of smart buildings emerges as a solution to create sustainable, efficient, resilient, active, and comfortable living and working spaces. This is achieved through intelligent resource use optimization, including the smart management of energy production, storage and distribution systems. Smart buildings operate by harnessing monitoring data and leveraging artificial intelligence algorithms and big data techniques. The integration of monitoring data with contextual information, such as building information modelling, physics, or simulation models, enhances the intelligent management of resources. Moreover, the incorporation of metrics like the smart readiness indicator promotes the adoption of smart buildings. This study delves into the significance of these techniques, expanding on existing research in the field of smart buildings. It integrates concepts of data enrichment, smartness, and user-centric approaches. Key findings provide insights into future opportunities within the sector, emphasizing the need for user awareness strategies, the development of new smart algorithms, and services that incorporate contextual data and the smart readiness indicator. The study also advocates for the widespread adoption of building digital twins.

### Abbreviations

Table 1 collects the abbreviations that have been mostly used along the survey.

## 1. Introduction

Most of Europe's buildings were constructed before the introduction of thermal and electrical energy performance standards [1] and, for that reason, a large stock of European buildings has a low energy performance. It is estimated that 97% of the buildings in Europe should improve their energy efficiency, as they are underneath the current standards [2]. This improvement is of utmost importance, as according to the Buildings Performance Institute Europe (BPIE), buildings account for more than the 40% of the energy consumption [2] and 36% of the greenhouse gas emissions in Europe [3].

Although the building stock in Europe is quite heterogeneous [1], approximately 75% of the buildings belong to the residential sector [2], and 85%–90% of these buildings will remain in 2050. Considering that only 3% of the buildings comply with the energy performance standards, a renovation wave becomes necessary [3]: on the one hand, with the aim of reducing 55% of the greenhouse emissions by 2030, according to the Climate Target Plan 2030 [4]; by adopting new digital technologies, following the digital strategy of the European Commission [5].

The strategy for long-term energy retrofitting for the building stock, stated by the energy performance buildings directive (EPBD) [6], promotes the digitalization of the building sector within a short-term evolution of the construction sector. Smart, connected and autonomous buildings should allow for remote control of heating and cooling, domestic hot water, renewable energy systems, lighting and appliances, among others. Buildings need to increase their capability to integrate information and communication technologies (ICT) so that elements involved in the operation of buildings can communicate with each other [7]. This includes the interaction between buildings, which can be considered as a more complex system, namely districts [8]. Technologies like Internet of Things (IoT), artificial dntelligence (AI) or

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**Table 1**
Abbreviations.

| Abbreviation | Description |
|---|---|
| AEC | Architecture, Engineering and Construction |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| BACS | Building Automation and Control Systems |
| BEMS | Building Energy Management Systems |
| BIM | Building Information Modelling |
| BIPV | Building Integrated Photovoltaics |
| BRP | Building Renovation Passport |
| CNN | Convolutional Neural Network |
| CPB | Cyber-Physical Building |
| CPS | Cyber-Physical System |
| DEMS | District Energy Management Systems |
| DNN | Deep Neural Network |
| DTR | Decision Tree Regression |
| EPBD | Energy Performance Buildings Directive |
| EPC | Energy Performance Certificate |
| eV | Electrical Vehicle |
| GAN | Generative Adversarial Network |
| HEMS | Home Energy Management System |
| HVAC | Heating, Ventilation and Air-Conditioning |
| ICT | Information and Communication Technologies |
| IFC | Industry Foundation Classes |
| IoT | Internet of Things |
| KPI | Key Performance Indicator |
| LCA | Life Cycle Assessment |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| ML | Machine-Learning |
| MPC | Model Predictive Controller |
| PCM | Phase Change Material |
| PMV | Predicted Mean Vote |
| PSA | Power-Shiftable Loads or Appliances |
| PSO | Particle Swam Optimization |
| PV | Photovoltaics |
| RFR | Random Forest Regression |
| SRI | Smart Readiness Indicator |
| SVM | Support Vector Machines |
| TBM | Technical Building Management |

big data become necessary in the smart buildings context to collect, manage and exploit buildings' data, as well as to integrate legacy equipment. In 2020, almost 225 million households were already considered to be smart, and this number is expected to increase up to 478 million by 2050 [9]. Indeed, the smart buildings sector is expected to grow 15.64% by 2050, enhancing energy efficiency and digitalization through an integrated approach that improves decision-making processes [3].

Interoperability plays a crucial role, aiming at enabling communication and data exchange mechanisms [10]. Standard data models are required to establish ontologies [11] as well as secured frameworks to exchange information [12]. Technologies such as blockchain offer the advantage of security and interoperability, while enabling new distributed energy services in which buildings interact with each other. One example is energy trading applications, with buildings exchanging energy to promote renewable energy generation [12].

Buildings should also adopt user-centric methodologies, i.e. integrating technology but having end-consumers as the core of the process [13]. Under this concept, new approaches in smart building automation like human-CPS (cyber-physical system) become key [14]. A fundamental aspect of CPSs revolves around empowering end-users. This empowerment goes beyond mere data visualization; it extends to the active management and parameterization of energy systems, allowing consumers to tailor them to their specific comfort requirements. In this context, the adoption of co-design and co-creation principles becomes imperative to accurately capture users' needs [15]. Consequently, placing end-users at the forefront, these principles serve as the foundation for the smart building [16]. It is clear that the building stock requires a deep renovation to transform the current construction sector into a smarter and more efficient one. Digital technologies play an important role in this transformation. In this work, the review of the current approaches in the application of advanced technologies (such as IoT, big data and AI) for a more efficient building stock. The current challenges in the building sector and the opportunities for the next generation of buildings are also described according to the state of the practice. Technology is rapidly changing and new methods are being applied; therefore, new approaches for smart building management are needed. Under this perspective, this review aims to analyse the current state of practice and the use of building models (such as building information modelling - BIM) to exploit the benefits of contextual data. Last but not least, novel metrics are also reviewed, such as SRI (smart readiness indicator), and how it helps to improve the energy efficiency of the building stock.

Most reviews in the field predominantly concentrate on the application of artificial intelligence (AI) techniques for optimizing smart building operations [17] or [18]. Some also delve into enriching data models with simulation, physics [19], or building information modelling (BIM) [20]. Notably, authors in [21] emphasize the importance of making smart buildings user-centric. However, previous reviews lack comprehensive coverage of the smart readiness indicator (SRI), BIM, and co-simulation techniques. This review addresses this gap by focusing on updating current practices within smart buildings, emphasizing the integration of three key concepts: BIM, user-centric approaches, and SRI. The novelty of this review is threefold: it provides updates on AI-driven strategies compared to existing reviews, it analyses the integration of BIM concepts, and it explores trends in the use of SRI as a smartness indicator, detailed in Section 4.1. It is worth noting that this survey concentrates on European countries, where SRI is applicable. The authors are unaware of similar initiatives outside Europe. Nevertheless, the analysis presented in this survey, with the exception of SRI, can be extrapolated to non-European countries.

The review is organized as follows. It is firstly discussed the definition of the concept of smart buildings (Section 2), and then explain the methodology that has been followed to perform the review (Section 3). It has consisted in analysing several European initiatives to identify current challenges and barriers in smart buildings within Europe. Then, based on those outcomes, a literature search has been executed, including a search for related surveys as well as recent papers (Section 4). Based on the analysis of those papers, current practices in technology implementation are explained in Section 5, while user empowerment is reported in Section 6. After this technological summary, opportunities for further research are discussed in Section 7. Finally, the conclusions are stated in Section 8.

## 2. Definition of the smart buildings concept

The smart building concept is not really new, it has been around for quite some time. For instance, "The Smart Building" journal by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) was created in 1984, and a paper by Williams [22] already treated advanced technology in building environment in 1987. Smart building is a trendy concept (more than seventeen thousand publications in the last three years according to Google scholar). However, there is no consensus in the definition of a smart building.

According to the European Commission [23], a smart building contains a set of features such as connectivity, ability to interact with objects, and the ability to be managed, controlled and automated in a remote way, becoming in pro-active. Many authors have provided their own view of the smart building concept, having different perspectives, as summarized in [24]. Osama [25] defines a smart building as a building with features like being responsive, effective (in terms of use of resources), cost-effective, fully automated, interoperable and multidisciplinary. Fouce et al. [15] remark the relationship between buildings in a smart city and the connection of the users and building facilities, and Al Dakheel et al. [26] complement it with multi-functionality

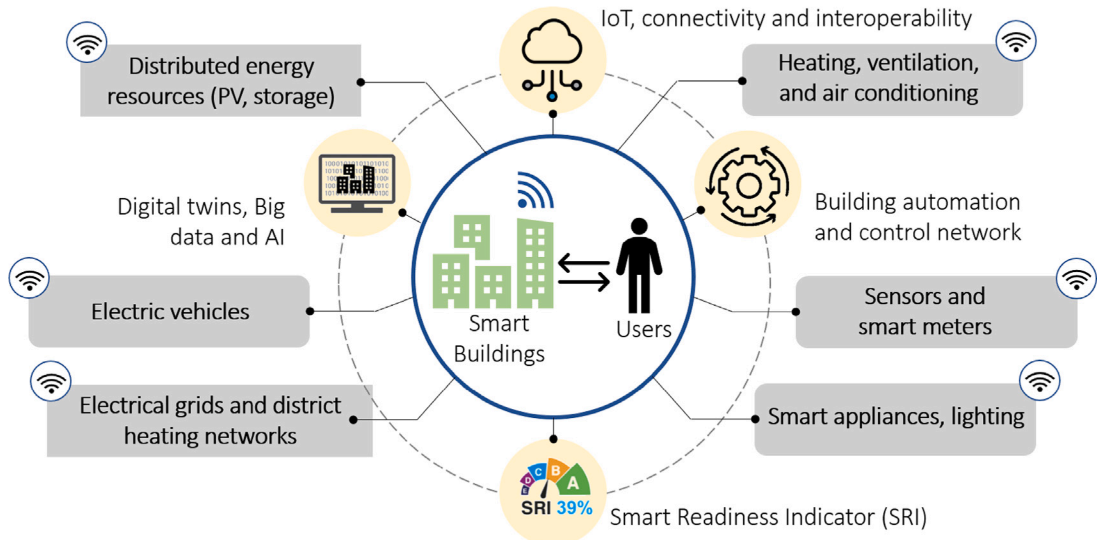


**Fig. 1.** Smart building concept and interaction with the environment.

(i.e., the ability to operate more than one function) and adaptability (i.e., the capability of learning, predicting and satisfying the needs of users and the stress from the external environment). The Building Efficiency Initiative [27] has also included the capability of delivering useful services to make occupants productive at the lowest cost and environmental impact over the building lifecycle.

Having in mind the different definitions, a set of common requirements, enabling technologies, and goals for smart buildings can be extracted. Fig. 1 provides the smart building concept from the authors' perspective. Smart buildings should be: (1) interactive with other buildings (i.e., smart districts) and other facilities/assets, such as electric vehicles (eV); (2) self-operative (i.e., provide certain level of automation) for pro-active operation of the heating, ventilation and air-conditioning (HVAC) systems and electricity grid; (3) connected & interoperable; (4) cost-effective in the use of the resources; and (5) interactive with users. This last point is related to the "Smart Users" concept [15], which leverages trained users to make better decisions based on data. Smart buildings meet these requirements to make a smarter use of both HVAC systems and distributed energy resources (renewable, storage) and eV through the application of advanced technologies (such as IoT, big data and AI) [28]. While the users are the core of the building, the ultimate goal is to address affordable living conditions (e.g. thermal comfort) for the occupants [2] to reach certain smartness degree according to a key metric, the smart readiness indicator (SRI), which is described in Section 3.3 and provides a quantitative value of the level of smartness of a building in multiple domains (e.g. heating).

In contrast to smart buildings, traditional structures exhibit a reactive nature. They lack connectivity and primarily rely on manual operation, with building facilities operating in isolation. Traditional buildings are not inherently prepared to adopt technologies such as the Internet of Things (IoT) and/or artificial intelligence (AI) without prior efforts in monitoring, digitalization, and/or the integration of datasets. Moreover, the implementation of smart services for energy-efficient operations requires foundational groundwork in traditional buildings.

## 3. Methodology of the review

Technology is rapidly growing, as stated by the well-known Moore's law. Due to this and the emerging techniques for building digitalization, this review has established a methodology based on the PRISMA approach (preferred reporting items for systematic reviews and meta-analysis) has been applied [44] to get to the current state of the art on smart buildings. The application of such a methodology lies in the following steps:

1. The research question, as established in the introduction, seeks to explore opportunities in advanced energy management strategies within buildings. Specifically, the investigation focuses on integrating BIM, co-simulation techniques, the SRI, and artificial intelligence AI.
2. Design the review protocol. Establishing the review protocol involves navigating the expansive literature on smart buildings. Initially, a thorough examination was conducted to identify challenges and barriers within the smart building context. Drawing insights from various European initiatives and European Commission reports, key conclusions are gleaned to discern current trends in the state of the art. This preliminary phase serves as a foundation, guiding the subsequent search for pertinent literature.
3. The literature search is systematically guided by the keywords identified in the previous step. This approach serves to pre-filter the substantial volume of research papers within the smart building context. In addition to articles sourced from the Web of Science database, supplementary references are identified, including PhD theses, to ensure a comprehensive and diversified exploration of the topic.
4. The selection of pertinent studies involved a comprehensive review of all acquired literature. During this process, papers not distinctly focused on advanced techniques in smart energy management of buildings were meticulously excluded. The description of this step is given in Section 4.
5. Data extraction, which is partially compiled in the Table 2, as well as Section 5. This section analyses and synthesizes the extracted relevant works to do a meta-analysis of the current practices in the advance energy management of buildings field.
6. Discussion of results through the key findings that are summarized in Section 7, answering the research question.
7. Conclusions and recommendations, provided in Section 8.

### 3.1. Identification of challenges and barriers for smart buildings

As a second step of the review methodology, current challenges and barriers in the digital buildings have been analysed. Four main sources have been used to analyse the current challenges and barriers in the digital buildings across Europe.

1. The SmartBuilt4EU initiative [16], which is a community of experts working in different research and innovation projects for

**Table 2**
Summary of the topics covered by the analysed surveys.

| Reference | Main topic | Techniques | Enriched model | Co-creation | User-centric | SRI |
|---|---|---|---|---|---|---|
| Yu et al. [17] | Smart energy management and optimization | Deep reinforcement learning | No | No | No | No |
| Fan et al. [29] | Smart energy management and optimization | Deep reinforcement learning | Simulation | No | Yes | No |
| Aguilar et al. [18] | Smart energy management and optimization | Multiple techniques | No | No | Yes | No |
| Farzaneh et al. [21] | Smart energy management | Machine-learning | No | No | Yes | No |
| Ala'raj et al. [30] | Smart energy management - HVAC systems | Multiple techniques | Yes | Yes | Yes | No |
| Himeur et al. [31] | Smart energy management | AI-based techniques | Simulation | No | Yes | No |
| Sharma et al. [32] | Wireless sensors & IoT | Machine-learning | No | No | No | No |
| Luo et al. [20] | Interoperable data for smart building operation | Deep neural networks | BIM | No | No | No |
| Alanne et al. [33] | Interoperable data for smart building operation | Deep reinforcement learning | Simulation | No | Yes | No |
| Kim et al. [24] | Smart home management | AI-based techniques | No | No | Yes | No |
| Alane et al. [33] | Smart home management | AI-based techniques | No | No | Yes | No |
| Aslam et al. [34] | Microgrid solar and wind energy generation prediction & load forecasting | Deep neural networks | No | No | No | No |
| Mabina et al. [19] | Renewable and electric energy generator | SVM & reinforcement learning | Physics | No | Yes | No |
| Khosrojerdi et al. [35] | Smart grid | AI-based methods & analytics | No | No | Yes | No |
| Hussain et al. [36] | Demand-side energy management | SVM & reinforcement learning | No | No | No | No |
| Lu et al. [37] | Building energy prediction | ANN | No | No | Yes | No |
| Barja-Martínez et al. [38] | Distribution and consumption domains | Multiple techniques | No | No | Yes | No |
| Neethirajan et al. [39] | Digital twins | Multiple techniques | No | No | Yes | No |
| Dong et al. [40] | Digital twins | Multiple techniques | No | No | Yes | No |
| Hasan et al. [41] | Cyber-Physical buildings | Deep neural network | No | No | Yes | No |
| Pan et al. [42] | AI for Construction sector | Multiple techniques | BIM & digital twins | No | Yes | No |
| Farghali et al. [43] | Energy savings | n.a. | No | No | No | No |
| This review | Smart buildings optimal operation | AI & ML techniques | BIM & co-simulation | Yes | Yes | Yes |

defining the future of smart buildings in Europe. Industrial as well as research and development organizations are engaged in this initiative. Four task forces have been set up: (1) Interaction with users; (2) Efficient building operation; (3) Interactions with the external environment; (4) Cross-cutting activities (security, business...).
2. European Commission (EC) technical reports published through different channels, like EPBD [6], publications or initiatives.
3. Other European initiatives like the Building Efficiency Initiative [27], created by Johnson Control in collaboration with the World Resources Institute, and formed by a community of experts in providing building efficient solutions. Another related source/initiative is the annex 81 European initiative [45], which deals with data-driven smart buildings.
4. The Smart Readiness Indicator (SRI) project [46], which aims to develop a new indicator for the assessment of smartness level of buildings.

Based on these sources, Section 3.2 focuses on the challenges and barriers of the application of digital advanced techniques for enhanced energy-efficient building management, while Section 3.3 deals with the specific challenges related to the recently adopted SRI.

### 3.2. Current status of the smart and digital building sector

The adoption of smart buildings is still far from reaching an outstanding number in Europe. BPIE realized an analysis of smart-ready buildings based on the criteria of energy-system-responsiveness, dynamic operation and efficiency, and tried to answer the question about whether Europe is ready for the smart building revolution with a clear negative answer [47]. Fig. 2 depicts the status of the European countries.No one is smart-ready, with front-runners like Sweeden, whose score is the highest (2.92 out of 5) [47], while the rest of countries presented a lower readiness indicator.

As indicated by the EC in its Climate Plan for 2030 [4], acceleration of the building renovation is crucial, and digitalization plays a pivotal role. Moreover, the COVID-19 crisis has presented a new opportunity to re-think and modernize the buildings [3] as human behaviour has changed and new comfort conditions are demanded. However, the smart solutions provide added value only if these are correctly understood and adopted by end-users [48]. While the current approaches are technology-push, customer needs should also be considered [45].

Current technology advances, such as cyber–physical systems (CPS), have the potential to reduce costs and overcome barriers to energy efficiency [45], but technology should be adapted to different users' profiles [48]. End-consumers have to participate in the energy transition (co-creation), but data must be understandable through analytics [49]. Also, the different perceptions of comfort conditions should be integrated to converge to energy-efficient building use.

Recalling the digital building, the integration of IoT sensors is the main enabler, but there is a slow deployment. From the 80% of estimated smart meters to be widely deployed in Europe by 2020 [47], only a 48% has been reached in 2020, according to Eurelectric association [50]. Additionally, the industry fragmentation includes multiple communication protocols, data formats and ontologies with diverse targets [51]. Although many initiatives are made to converge to standard communication protocols, the IoT deployment is still vendor dependant [10].

The heterogeneous nature of the data related to buildings makes the integration of interdisciplinary domains very complex [52]. That is the case of the integration of building information modelling (BIM), which is a work methodology in the building sector to virtualize building assets (e.g. envelope, pumping system, etc.) or sensor timeseries. In addition, industrial players are not yet ready for these technologies [9]. For instance, BIM is far from being fully adopted in Europe. According to a report from the EC [53], Austria is the leading country in Europe with 3.5 marks out of 4, but other countries like Portugal or Belgium do not have legislation/regulation in this topic.

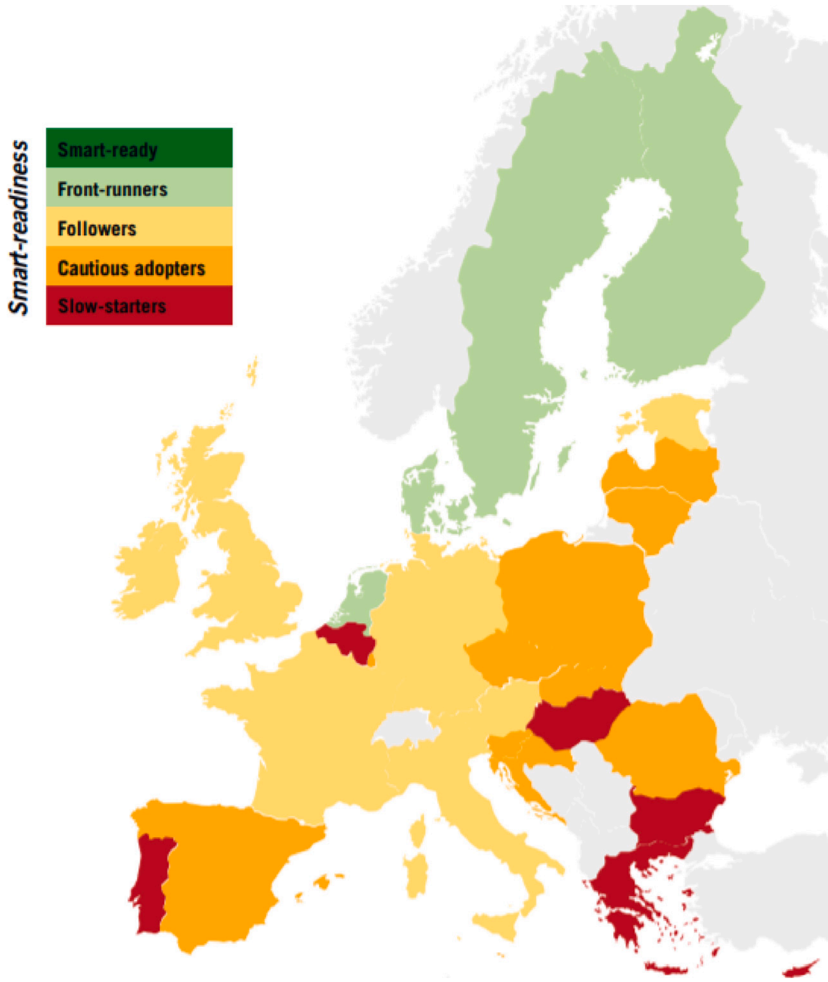


**Fig. 2.** Readiness for smart technologies in buildings in European countries [47].

IoT technologies are usually combined with building simulation [9], the so-called co-simulation, to complement missing data such as energy inertia. However, neither the IoT nor simulation tools consider the user behaviour in the results. Also, BIM frameworks are providing benefits thanks to the use of digital data in the built asset. Digital building logbooks (DBL) [54] are encouraged to create repositories of common building data (i.e., static data such as BIM and dynamic data coming from smart meters) over the building life cycle. DBL facilitates data sharing, trust and even interoperability, bringing all the stakeholders to the same table.

The convergence of all these data paves the way to the building digital twins, which promise more effective asset design, operation and maintenance [55]. One of the major advantages of digital twins is the increase of collaboration and optimization of the energy performance [55]. Its implementation through CPS supports the capability for creating the demanded user-interaction, as well as the development of advanced analytics by big data and AI techniques [45].

Reaching this vision requires adding intelligence from the beginning of the design phase through to the end of the building useful life. Standards like EN-15232 [56], through the technical building management (TBM) and building automation and control systems (BACS), focus on the smart operation and maintenance of buildings. IoT, big data and AI become enablers in the energy transformation of buildings [57]. These technologies are supporting the creation of new standards and tools to integrate data on future climate conditions and risks (adaptation to climate change) into all aspects of decision making along the built environment value chain [58]. Next generation of buildings must be data-driven, applying modern ICT approaches [45], converging to level A in EN-15232 standard [56].

In short, the main challenges and barriers that limit the implementation are listed:

- There is an absence of significant customer demand/awareness, skills and/or access to data [45] and monitoring feedback. Technology is not user-friendly enough to target the general public and data-driven techniques are still complex [48] to comply with occupants wishes.
- There is a low penetration of BIM methodologies [53] for digitalization of buildings along the life cycle [59].
- There is low quality and insufficient amount of data to stimulate renovation and deployment of smart services [60] due to the reduced integration of IoT sensors [47].
- There is a need for the promotion of digital building logbooks [54], including digital twins as the enablers for optimized energy performance of buildings [55] in combination to the CPS and new technologies like big data and AI [45].
- The application of smart energy operation and maintenance techniques should be fostered to achieve a more climate-friendly building stock according to the EN-15232 standard [56].
- Big data and artificial intelligence techniques should exploit the big amounts of data that are being currently generated by buildings.

### 3.3. The smart readiness indicator

New technological approaches need to be complemented with assessment methods of the smart operation and energy efficiency of buildings. The current building certification procedure is based on the so-called energy performance certificate (EPC) schemes [6]. Five overarching EPB standards (ISO 52000-1, 52003-1, 52010-1, 52016-1 and 52018-1) [61] support the assessment methods of the energy label. These methods are used to quantitatively predict annual building energy demand based on a static calculation rather than on the dynamic evolution of the energy use [60]. The next generation EPC should rely on combining BIM, big data techniques and building smart-readiness indicators [60].

The smart readiness indicator (SRI) [46] was introduced in the 2018 revision of the EPBD [6]. The SRI is an indicator whose main target is to allow rating the smartness of buildings and is focused on the following principles [46]:

- Capability of buildings to adapt their operation to the occupants' needs.
- Capability of buildings to adapt their operation in reaction to signals from the grid (energy flexibility).
- Energy efficiency and overall performance optimization.
- Enhancement of awareness amongst building owner and empowerment of them.

SRI should be the mapping and assessment tool for the smartness upgrade of the existing building stock [61]. SRI should be embedded into the existing EPC schemes, developing a digital building passport framework [2], where data from monitoring (including legacy equipment) should be considered. This integration will promote the renovation roadmaps through the building renovation passport (BRP) [62], which will integrate the energy audits with the actual performance of buildings. Its result will guide the interventions for the benefits in terms of reduced heating bills, comfort improvement and $CO_2$ reduction. The BRP takes advantage of the previously mentioned digital logbook [62] as a central data repository to obtain information in energy consumption and production. Nevertheless, the traditional ways of static calculation of the energy performance ratings should be replaced by dynamic and adaptable values according to the real building operation.

To sum up, the SRI-related challenges in the smart building context are:

- Integration of SRI-driven energy management capabilities.
- Inclusion of SRI as indicator in the EPC for dynamic and adaptable certificates.
- Making the users part of the smart building transformation and empowering them with helpful information to take better-informed decisions.

## 4. Literature review: State of the practice

The smart building concept has currently a wide application with lots of actual investigation works from different disciplines, such as the architecture, engineering and construction (AEC) industry, ICTs and artificial intelligence among others. In this work, the focus is on the application of ICT solutions (e.g., big data, machine-learning (ML) or artificial intelligence (AI)) for transforming the current building stock into a smarter one. The literature search is centered on papers within the specific application field, aligning with European trends. It explores how research conducted outside of Europe may also be applicable within the European context.

As technology is exponentially growing, only results since 2019 have been included with the most updated research works. The literature exploration has been performed through the Web of Science database, filtering by scientific articles. The query that has been applied follows the decision tree that is depicted in Fig. 3 (step 3 of the methodology), where keywords extracted from the analysis shown in Section 3 guided the paper search. In this sense, the root for seeking is the smart building topic itself, following an "or" logical query as "Smart Buildings or Smart Districts", obtaining seventeen thousand nine hundred eighteen results on 22 July 2023.

Each branch of the decision tree represents a logical "and" to combine queries and making more accurate look-ups. For instance, the left branch of the figure represents the search "(Smart Buildings OR Smart Districts) AND (Energy efficient buildings OR Energy efficient Districts) AND Smart Energy Management AND (Machine-learning OR Artificial Intelligence)". By applying the same reasoning for the rest of keywords, the number of papers found is shown in Fig. 3, reaching a final selection (in the terminal nodes of the tree) of a total of one hundred seventy three articles, including previous surveys as well. In this last case, only surveys in the last two years and a half (i.e. 2021 and 2022 and mid 2023) related to energy management and the application of AI in smart buildings have been selected.

This review is focused on how AI and big data are supporting smart buildings in terms of enhanced energy efficiency. According to this criterion, results that did not focus on this topic were discarded. The literature search has been complemented with the results of the four task forces from SmartBuilt4EU [16], three theses on the topic of AI and big data for building energy management, and other initiatives described in the previous section (i.e., annex 81, BPIE, etc.). After curating the paper search and including these complementary references, a total of one hundred ninety five references have been used for this review.

### 4.1. Analysis of existing reviews and contributions of this survey

As illustrated in Fig. 3, there are many results in terms of smart buildings. In the last year and a half (January 2022–July 2023), 22 reviews have been published in the field of energy management and application of AI in the smart building context. Table 2 summarizes the results of the analysis of main reviews along 2021–2023 and includes the main contributions from this work, summarized in the integration of BIM and co-simulation principles, co-creation, user-centric approaches and SRI-driven strategies. The following bullets provide an explanation about the meaning of the columns:

- Main topic that is addressed in the review, i.e., the context of analysis of the survey. The preceding reviews predominantly concentrate on smart energy management and optimization topics, primarily employing AI techniques like reinforcement learning. Another key focus area is the integration of data through interoperability features, addressing the use of multiple data sources to enhance data availability. Furthermore, previous surveys delve into the examination of the smart grid and the integration of renewable energy sources within smart buildings. Lastly, as a central aspect of this study involves the integration of BIM, an additional topic explored is digital twins, where BIM commonly serves as the foundation for creating digital building twins.
- AI or ML techniques/technologies that are discussed in the review, either being a single method or a combination of techniques.
- Enriched model, which identifies whether the review analyzes the use of any building model (e.g. BIM, simulation, physics, mathematical equations...) as a complement for the AI/ML technique in order to enrich the information for the decision-making processes.
- Co-creation, which indicates if the survey analyzes whether users' feedback is introduced in the design of the energy management strategies of the different proposals or not.
- User-centric, which indicates whether the survey analyzes if the proposals have an impact on the users (e.g. improved thermal comfort), or just focus on physical parameters like energy efficiency.

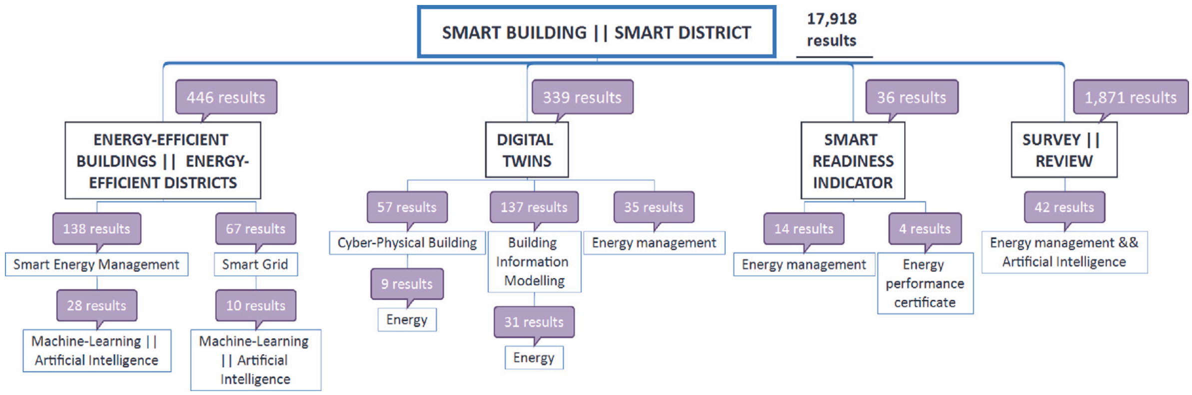


**Fig. 3.** Decision tree for the systematic literature search.

- SRI, which indicates whether the review analyses the use of this indicator for the improvement of smart building energy management strategies by the different proposals.

As anticipated, different approaches have been analysed from multiple perspectives and topics. As observed, none of the previous reviews considers the SRI as part of the AI-based energy management strategies, being this one of the major contributions of the current review and how SRI can be exploited in the building energy sector. According to the European directives, SRI should be the driver of the new approaches in the energy management of smart buildings [6], through the so-called smart-ready services [46], which are applicable to different pillars: thermal facilities, appliances, flexibility, renewable, smart grid... However, the energy management and optimization strategies are mostly focused on the application of advanced technologies, such as reinforcement learning [17,29] or support vector machine (SVM), fuzzy networks or regression, among others [18,31]. Complementary, the bottleneck in these applications lies in the complexity of the data-driven models due to non-linearity, as well as the limitations of physical models [38].

The implementation of deep RL strategies allows the control at different building scales (i.e., single and multiple building energy subsystem(s) and microgrids) [17] to minimize energy costs while maintaining comfort levels. Nevertheless, comfort is not a trivial task and some approaches are modelling thermal comfort of users. Hasan et al. [41] analysed the use of generative adversarial networks (GAN), convolutional NN (CNN) and tree-based CNN to predict personal thermal comfort. In this same path, Farzaneh et al. [21] surveyed the combination of data with building occupants to foster the end-consumer participation in the AI-based algorithms, as well as Ala'raj et al. [30] via ANN (in fact, deep neural networks). Even though end-consumer comfort is considered, for instance via users' feedback [17], the previous reviews still do not fully consider the co-creation aspects. This survey puts the user in the centre of the smart management strategies, analysing the co-creation and co-design methodologies to ensure users' interaction.

In this line, adaptable smart thermostats and decentralized approaches are part of the current state of the art to provide solutions in terms of prediction, classification of consumers or load profiling [24]. Other approaches are facility and asset management, energy systems management, fault detection or load forecasting. Smart grid interaction for electricity flexibility, the connection of appliances, such as eV, and shiftable loads allows new ways of smart energy management moving towards detailed system integration [33].

Moreover, the use of model-based controllers (pr, similarly, model-predictive controllers MPC, also known as grey box models because they are combining building physics with data-driven models, as indicated in the next section) are not fully deployed. Many of the reviews are focused on model-free strategies, although some authors deal with the co-simulation approaches [29] or building physics [19] or integration BIM [20,42] to move the paper-based work towards online management. Nevertheless, it is not common across the listed reviews to analyse, above all, the BIM or simulation models into the smart management strategies. The authors usually mention the challenging tasks of including simulation models: (a) difficulty in developing explicit building thermal dynamics; (b) uncertainty in system parameters (e.g., renewable generation output, outdoor temperature, and number of occupants); (c) lack of interactivity between thermal zones even if they are correctly identified [17]. Aguilar et al. [18] pointed the use of an optimized building envelope model using a multi-criterion optimization approach. However, it cannot be neglected the model-predictive control (MPC), which is also discussed in this review and how the integration of these data move forward the building digital twins and cyber–physical systems to better decision-making strategies. Real-time applications are being analysed to operate and train algorithms to learn about different cause–effect scenarios [39]; therefore, AI algorithms are able to discern between useful and non-useful information [39] to provide functionalities like demand-side management (DSM) or load scheduling strategies. Additionally, digital twins require the user's behaviour integration [40], but the occupant behaviour datasets are not large enough yet. Extending digital twins, the cyber–physical buildings (CPB) [41] focus on the combination of real-time data, AI-based techniques and users' interactions.

Thus, the integration of heterogeneous data sources becomes pivotal, as highlighted by Sharma et al. [32], Luo et al. [20] or Alanne et al. with special emphasis in the interoperability to deploy AI techniques such as deep neural networks or reinforcement learning, introducing the concept of "cognitive" building [33]. In short, three main axes are required in smart energy management: monitoring, analysis (pre-processing) and decision-making [18,20,32,33]. Some techniques like fuzzy c-means or k-means clustering algorithms were used to group signals and facilitate fault detection and diagnosis tasks [29].

Finally, the application of AI/ML techniques is still complex, in the sense of understanding data-driven models due to the parameters that are fine-tuned within the target domain [42]. Many surveys discuss about the application of reinforcement learning and artificial neural networks for predicting the capability of renewable sources to cover the electricity demand at buildings [19,34], providing different conclusions in terms of more accurate techniques. Depending on the approach, it is discussed the accuracy of SVM for energy forecasting [36] or the demand for electric vehicle (eV) charging into account to cover resilience or efficient operation by enabling energy audit [35]. In other cases, as highlighted by Barja-Martínez et al. [38], additional techniques such as linear regression or random forest are more predominant in the operation and monitoring of smart buildings. Moreover, the introduced bias due to the current data-sets is critical [37].

All these aspects are very relevant at this moment, as remarked by Farghali et al. [43]. In these times with several crisis, such as the COVID-19 or the Ukraine war, energy becomes in a scarce resource. Techniques like deep neural networks. among others, may reduce 18.97–42.60% of energy consumption in buildings worldwide. Although this is not only limited to the use of AI techniques, but also other methods like big data analytics for better-informed decisions, where smart grid analytics supports the decision making in residential buildings for energy savings (no results yet).

According to the addressed topics and challenges previously described, this review provides insights with respect to the analysed surveys as follows.

1. SRI is far from being the driver of the smart energy management strategies, but it is not included in any of the analysis of the previous reviews. It is still considered as an isolated indicator to evaluate the readiness of the buildings, but not as the decider of the most intelligent strategy. This review discusses how this SRI should be used in the future building strategies.
2. Although the analysis of model-based methods (i.e. AI/ML techniques complemented with BIM, simulation or physics), is increasingly discussed in the reviews, its integration, due to the complexity of data interoperability, is still not fully developed, even though its benefits in several prevalent building domains. This review provides more insights in how grey box approaches would expand the smart building sector, in terms of digital building twins and CPB.
3. Several authors highlighted the importance of the occupant behaviour within ML algorithms. However, this is neither considered in benchmarking nor in physical models of the HVAC assets [33]. Co-creation and co-design aspects are analysed in this review and how to address end-users to provide user-centric approaches for better-informed decisions and management strategies, fostering the interaction users and buildings.
4. Unlike many literature reviews, which are primarily focused on AI techniques, this review is more centered into AI-based smart services for smart buildings; not just comparing AI techniques, but strategies to transform buildings into smarter agents within the energy environment.
5. This review also compiles and provides a critical analysis of the current state of the art in the smart building sector.
6. Last but not least, this review identifies a set of future research lines and opportunities for transforming building stock into a smarter one.

## 5. Advanced smart energy management techniques for smart buildings

There is a trend to use AI and big data technologies to improve the building energy performance [28]. These technologies allow including prediction of energy demand and generation, as well as modelling building behaviour for more precise operation. However, many of the existing reviews are only focused on the application of data-driven models without considering the use of contextual information, such as the case of BIM to deploy the digital building twins. SRI should be the driver for future smart buildings. This section reviews the current trends in the application of AI and big data for advanced energy management strategies, focusing on thermal energy facilities at home, building and district levels, and on smart grid integration (i.e. electricity). Additionally, the combination with BIM and SRI addresses energy-efficient and pro-active buildings. Current AI-based energy management strategies being deployed in smart buildings are firstly analysed. Then, the integration of BIM and Cyber-Physical Systems, and finally, SRI methods for enhanced energy management are discussed are reviewed.

AI can buildings with new skills: e.g., self-learning, self-decision-making, and self-updating [28]. Many different techniques have been applied and analysed, such as support vector machines (SVM), artificial neural networks (ANN), decision trees and reinforcement learning, as part of the energy management strategies for smart buildings [17,28,40,42]. Within this section, the current state of the practice in thermal energy and electricity are tracked (in Sections 5.1 and 5.2, respectively), thus complementing the previous surveys with the outcomes of recent works.

### 5.1. Smart management of thermal energy facilities

Thermal energy accounts for 50% of the final energy use in EU buildings [63]. While focusing only on the residential building stock , thermal energy usage increases the statistics up to two thirds of the final consumption. Thermal energy refers to the energy needed for space conditioning (heating and cooling), as well as domestic hot water. Currently, natural gas is the largest primary energy source (46%) [64]. The increase of the energy efficiency in the HVAC elements becomes then pivotal for a decabornised building stock. AI, ML and big data play an important role as they can provide optimal control strategies and lead to better-informed decision-support systems to reduce the final energy use.

Fig. 4 illustrates the three main levels that are usually differentiated in smart energy management: (a) home energy management systems (HEMS); (b) building energy management systems (BEMS); and (c) district energy management systems (DEMS). As highlighted by [8], the DEMS operates at a level involving the interaction between buildings and their environment. This necessitates advanced energy management strategies to cater to the demands of multiple buildings while ensuring optimal comfort levels. Therefore, although this level extends beyond a singular smart building, a smart building, as defined, should possess the capability to be proactive and engage with its environment. This characteristic forms a key focus of interest in this paper review.

#### 5.1.1. Home energy management systems (HEMS)

Home energy management system is the basic level on the energy management hierarchy, where dwelling level facilities are the controllable loads, such as washing machines or dishwashers, among others. In the thermal context, the main basic asset is the thermostat, aiming at thermal comfort, but also, air-conditioners or electric water heaters. All of them are known as thermostatically controlled appliances [65]. Nevertheless, there is a lack of interoperability in the HEMS that needs to be overcome to facilitate the energy management [66]. Table 3 compiles the literature focused at HEMS, indicating the application field, techniques employed and whether home models are used. This table confirms that only TRNSYS models (a reference simulation tool) [67] are employed in one case, while BIM is also used in another work. The rest of studies do not exploit the benefits of including model-based approaches (see Section 5.3).

Several works have investigated the optimization of the final energy use when employing thermostats to assure thermal comfort. Wang et al. [68] developed a rule-based control algorithm to enhance comfort according to the ASHRAE-55 standard [81]. It includes an adaptive temperature set-point depending on a random occupancy pattern generator, as well as co-simulation strategies with EnergyPlus software (a simulation tool similar to TRNSYS) [82]. It demonstrates 90% of user satisfaction and approximately 14% of energy savings. Other authors like Abdulgader et al. [69] bet for the application of machine-learning techniques like multiple linear regression (MLR), support vector regression (SVR), random forest regression (RFR), and decision tree regression (DTR) to calculate thermal comfort by using Fanger method [81] (a method to evaluate thermal feeling). RFR presented the best results in terms of root means square error (RMSE) and $R^2$ metric while SVM offers the lowest mean absolute error (MAE).

In the case of Naseem et at. [74], they researched on a machine learning-based temperature set-point estimator using a predicted mean vote (PMV) approach, while modelling the building demand in the EnergyPlus software. The results of combining ANN and EnergyPlus

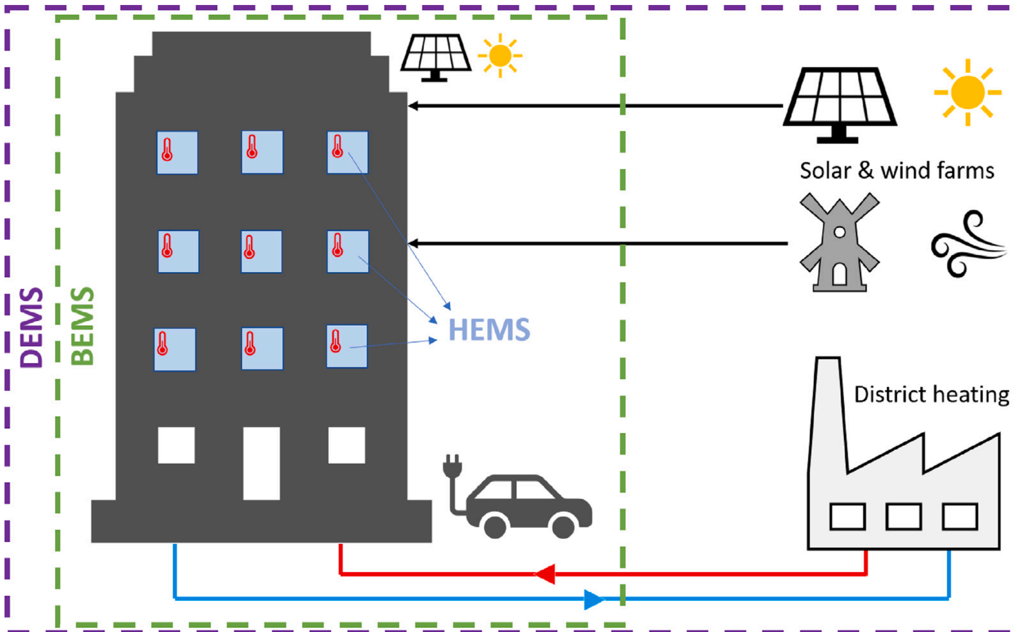


**Fig. 4.** Levels in the smart energy management of buildings.

**Table 3**
Home energy management systems.

| Literature | Application field | Technologies | Enriched model? |
|---|---|---|---|
| Duman et al. [65] | Smart thermostat | Fuzzy logic | No |
| Wang et al. [68] | Smart thermostat | Rule-based control | No |
| Abdulgader et al. [69] | Smart thermostat | Various regression methods | No |
| Merabet et al. [70] | Smart thermostat | Fuzzy logic | No |
| Hakimi et al. [71] | Smart home appliances | Rule-based control | No |
| Gao et al. [72] | Thermal comfort | Feedforward neural network | Yes, TRNSYS |
| Abdelrahman et al. [73] | Thermal comfort | K-Nearest Neighbour & Random Forest | Yes, BIM |
| Naseem et al. [74] | Thermal comfort | Model-predictive controller with ANN | Yes, EnergyPlus |
| Yang et al. [75] | Indoor temperature (comfort) | Multiple techniques | No |
| Traboulsi et al. [76] | Indoor temperature (comfort) | Multiple techniques | No |
| Verma et al. [77] | End-user comfort | Multiple techniques | No |
| Chinthavali et al. [78] | Home energy profiling | Optimal controllers | No |
| AlZaabi et al. [79] | Home energy prediction | Data fusion with ANN & fuzzy | No |
| Ramadan et al. [80] | Home energy assets consumption | factorial hidden Markov model | No |

(MPC) obtained 17.20% less energy use during winters and 14.67% less energy use during summers than a simple on/off controller. However, as stated by Lee et al. [83], one unintended consequence could be the load synchronization due to the similar operation of smart thermostat controls. Besides, current practices do not consider real occupant schedules. Another challenge is identified by Merabet et al. [70], who stated that comfort calculations based on the ASHRAE-55 standard present discrepancies between the real and predicted values. Personal interaction is thus necessary to better analyse thermal comfort, and they concluded that fuzzy logic is an appropriate tool that models the users' behaviour in the buildings [70].

Duman et al. [65] also implemented a fuzzy logic thermostat, but combining the electricity price and renewable production to reduce the costs within an air-conditioning system. Their results demonstrate an increase of the self-consumption (up to 93%) and reduced costs of 44% from the original values. Air-conditioning is one of the controllable loads of the thermal management at home, but its coupling with the grid should be considered. Hakimi et al. [71] proposed a hybrid home management system where controllable and non-controllable loads are grouped. Unlike other researches, the design of the algorithm is based on a mathematical formulation, which models the electricity and thermal storage systems, appliances and production facilities, while decision-making is rule-based [71]. The algorithm reaches the equilibrium by balancing the generation sources to supply all thermal and electrical loads, storing the surplus of energy.

Thermal comfort is, as observed, a key aspect to be ensured at HEMS level. Gao et al. [72] developed a feed-forward neural network, complemented with bayesian regularization and deterministic policy gradients, to learn and predict indoor thermal comfort conditions. Their proposal led to 4.3% of energy savings and thermal comfort improvement of 13.6% [72]. However, the model requires some data (e.g. radiant temperature), which is usually not monitored. Same happened with the work by Abdulgader et al. [69], which requires the use of data such as human metabolic rate (calories burned by human body), and thus needs to be estimated. Yang et al. [75] compared six algorithms to predict the indoor temperature, where the autoregressive integrated moving average (ARIMA) method showed the most promising results. Abdelrahman et al. [73] made use of BIM to extract building features, integrating the spatial characteristics, achieving up to 0.93 of validation accuracy.

However, user comfort cannot be limited only to thermal aspects, but also visual and indoor environmental quality should be considered. To enhance these factors, Verma et at. [77] compared several optimization techniques (genetic algorithm, bat approach, artificial bee colony and neural networks (NN)) in combination with a fuzzy temperature controller and a linear regression model. The authors demonstrated an energy consumption reduction of more than 2300 kWh/year, with the best performance for the bat algorithm, and comfort indexes (merging thermal, visual and environmental quality) higher than 0.83 [77].

**Table 4**
Comparison between building thermal modelling categories.

| Model | Data requirements | Complexity | Applicability |
|---|---|---|---|
| White-box | Only for model calibration | High: Detailed physical model | New buildings or no data available |
| Black-box | Historical data-set | Medium: Apply machine-learning | Highly monitored building |
| Grey-box | Medium size data-set | Medium: Simplified building physics + ML | New buildings or minimum monitoring |

There is a key question about how the energy profiles change under unexpected situations such as the COVID-19 pandemic. Chinthavali et al. [78] have analysed how home assets needed to be re-adapted under these circumstances in multiple households. The use of programmable thermostats reduced the baseline from 44% to 31% of the energy consumption. Besides, indoor temperature variance due to pandemic situation was researched by using three methods, linear regression, multilayer perceptron and random forest [76].

These works are complemented with home energy prediction techniques that allow forecasting energy needs at home level. For that end, methods like data fusion [79], which consists of merging data from multiple sensors, are used. While the ANN technique monitors the energy consumption, the fuzzy logic allows decision-making inserting the uncertainties of the users. The results shows improved accuracy of 92.3% (true positive vs total population).

However, data (either energy consumption or comfort) are not always available, limiting the capabilities for research; hence, techniques are required to interpolate data-sets. Ramadan et al. [80] developed an algorithm to estimate energy consumption by home assets to implement the management system. The non-intrusive load monitoring (NILM) method, using a factorial hidden Markov model (FHMM), was applied to obtain the status of the appliancesappliances status based on the overall signal from the smart meter. Data imputation procedures were applied to complete the data-sets.

*5.1.2. Building energy management systems (BEMS)*

The next hierarchical level is the building, which consists of the aggregation of multiple dwellings. Building level can be considered as a condominium or a set of dwellings using a common renewable energy production facility or central heating systems. One of the main activities at the building level is the management of these common facilities to keep similar comfortable levels in all dwellings, at the same time that effective and efficient services are dealing with building energy savings due to better performance [84]. Daissaoui et al. [84] proposed the joint use of IoT and big data (hadoop and spark framework) to extract knowledge from data. Data play a crucial role in this type of applications, but the optimal selection in sensor distribution within the building is desirable [85]. The use of the Web of Things (WoT) enables the interoperability to combine data from indoor air, HVAC and water pumps coming from various vendors to support the creation of energy models [86].

A key aspect at the BEMS level is thermal modelling. Thermal modelling extracts the characteristics of the thermal behaviour of the building to improve its performance. Three main approaches are considered [87]: (1) co-simulation through the use of simulation tools which model the physics of the building [17,40], what it is called the "white-box" model; (2) data-driven models using machine-learning [88], "black-box"; (3) the combination of physical and data-driven models ("grey-box") [89]. Table 4 gathers these three levels with the pros and cons and how the model should be applicable depending on the context.

In the context of thermal modelling to predict the demand, Benavente-Peces et al. [88] introduced various machine-learning approaches (logistic regression, decision tree, linear discriminant analysis, SVD (singular value decomposition), k-neighbours and Gaussian NB (naive bayes) to determine the most important parameters affecting the demand of a building. These are the climate, age of building, envelope features and surface. In [90], an event-triggered reinforcement learning algorithm was deployed with the aim at reducing the complexity. The problem was characterized by a semi-Markov decision process and the results showed optimal thresholds of 12.5 °C and 17.5 °C to switch on/off, respectively, manifolds in the control policy [90].

Luo et al. [91] characterized the building thermal losses and infiltration, as well as the effects of heat transmission between adjacent spaces and floors. The authors demonstrated the effects in 12 zones within an office building in United Kingdom, where different set-points were set in such zones. Artificial NN were used to train the model according to different outdoor conditions, which were clustered by k-neighbours method. Using the same technique, Liang et al. [92], unlike Mohseni et al. [93] who used reinforcement learning, estimated the heating and cooling loads by optimizing the algorithm with hunger games search optimization, among other hybrid algorithms, reaching very good values of $R^2$ (higher than 0.94) and MAPE (mean absolute percentage error) (lower than 0.08).

Li et al. [87] studied the application of grey-models for thermal demand prediction. The multiple elements (i.e. envelope, zones, HVAC systems...) of the building were modelled as resistance-capacitor (RC) to combine them to represent the building thermal features. These models covered multiple building perspectives (e.g. comfort, water management or energy management, among others), as identified by Himeur et al. [31]. A similar approach of an RC model was followed by Raman et al. [94], who implemented a MPC (model-predictive controller) that incorporated humidity and latent heat, increasing the effectiveness both in winter and summer independently of the climate zone. Chaganti et al. [95] combined the building features (glazing, orientation...) with ensemble methods (three random forest together with a final voting process to make the final decision). The results proved the increase from 0.95 to 0.99 of the $R^2$ parameter, reducing the standard deviation of $R^2$ parameter along simulation time.

One important aspect to be managed in the BEMS is the storage (either thermal or electrical), which is usually combined with solar air or water heating systems (as it will be also described in Table 8). In this line, He et al. [96] compared different techniques (ANN, fuzzy, neuro-fuzzy or SVM) to predict storage behaviour (water temperatures, thermo-physical features or performance). One of the main conclusions of the authors was that fuzzy logic can absorb uncertainties of the weather forecast.

The electrification of the thermal energy systems should be also considered. This is mostly known as sector coupling [97]. From traditional thermal systems like gas boilers, new trends are the integration of heat pumps through power-to-heat technologies [98]. Duhirwe et al. [99] addressed the integration of heat-pumps with storage and photovoltaic (PV) production to enhance thermal comfort. To overcome the sector coupling specific aspects, a cascade of deep learning algorithm demonstrated the capability of reducing 10% of the final energy compared to baseline. The first stage decides when to store or use thermal energy according to electricity prices, while second stage treats the electrical side [99].

Alanne et al. [33] studied with the integration of multiple energy facilities (heating and cooling, ventilation, lighting) to train autonomous building, but did not integrate human behaviour. Korkas et al. [100] also integrated multiple building loads (heating, PV, energy storage and eV) in an approximate dynamic programming (ADP) method. This method improved results by about 9%–18% compared to a rule-based method and obtained results similar to those of open-loop optimization (OLO) controllers, but reducing iterations by 10 times (implying a lower computational load).

Table 5 summarizes the bibliography for BEMS. This table provides the technologies applied by other works, as well as the application field and the thermal model type from Table 4.

**Table 5**
Building energy management systems.

| Literature | Application field | Technologies | Model type |
|---|---|---|---|
| Daissaoui et al. [84] | Facilities & energy management | IoT + big data | Black box |
| Ibaseta et al. [86] | Energy monitoring | WoT | Black box |
| Benavente-Peces et al. [88] | Thermal modelling | Multiple techniques | Black box |
| Luo et al. [91] | Thermal modelling | k-means + artificial NN | Grey box, TRNSYS model |
| Li et al. [87] | Thermal modelling | Simulation | White box, resistance-capacitor |
| Duhirwe et al. [99] | Heat-pump optimization | Cascade deep learning | Black box |
| Himeur et al. [31] | Heat-pump optimization | Cascade deep learning | Black box |
| Raman et al. [94] | HVAC optimization | MPC | White box, resistance-capacitor |
| Chaganti et al. [95] | Heating & cooling prediction | Ensemble learning | Black box |
| Liang et al. [92] | Heating & cooling loads | Artificial NN | Grey box, building physics |
| Mohseni et al. [93] | Heating & cooling loads | Reinforcement learning | Grey box, building physics |
| Haji et al. [90] | Model-predictive control | Reinforcement learning | Grey box, E+ |
| He et al. [96] | Thermal energy storage | Multiple techniques | Black box |
| Alanne et al. [33] | Autonomous building | Deep learning | Black box |
| Korkas et al. [100] | Building energy management system | Approximate dynamic programming (ADP) | Grey box, simulation model |

#### *5.1.3. District energy management systems (DEMS)*

The highest level corresponds to the district management, which includes sets of buildings and interactions between them [8]. The action-reaction between the buildings and the environment should be considered [101], such as district heating networks or solar/wind farms (Fig. 4). At this level, decision-making tools are enhanced with the objective of making a more efficient use of natural resources [8]. Although this level extends beyond an individual building, the district level, encompassing interactions between multiple buildings, is deemed significant for this review. It holds importance because it necessitates the management of both generation and demand sides for achieving optimal energy distribution.

Within DEMS, usually, the generation system operators configure the operation parameters based on experience and these are adjusted with data. Then, decision-making tools help in the optimization of the operation. Marinakis el at. [102] proposed a big data architecture where all the data artifacts coexist to support better-informed decision making procedures. The authors bet for a solution where data-sets are classified and dimensionality is reduced to provide simpler energy models as services. The use case presented in [102] presents a multi-linear regression (i.e. combination of several linear regression models) to notify users about anomalies in the energy facilities with an accuracy of 95%. Luo et al. [91] also proposed a big data platform with analytics calculation capabilities. The management of timeseries and historical data resources were combined with simulation tools (TRNSYS in the case of [91]) to be able to predict heating and cooling demands of buildings sets. This simulation-model-based schema was complemented with hybrid ML techniques where clustering, more specifically the k-means algorithm, determined the thermal zones of the building and an artificial NN determined the energy demand for each zone, which is indeed one of the recommendations of the EPBD [6] to enhance thermal energy efficiency and comfort in buildings.

These decision-making strategies rely on the capabilities for information exchange amongst the various district elementsThe the relationships should be established, such as explained by Saba et al. [103], through an ontological solution for energy intelligent management. Thanks to the ontology relations, a set of rules can be defined to properly schedule the energy resources, dealing with savings of 4.58%. One of these relationships is the district heating. In this way, Lumbreras et al. [104] developed a multivariate regression to estimate load forecast for 42 stations (distribution element at building level), obtaining $R^2$ values higher than 0.7 and nearly 0.9 in most of the cases.

DEMS allows using resources more efficiently. García-Fuentes [8] developed a fuzzy multi-criteria decision-support system for districts energy management strategies. Ibaseta et al. [86] also highlighted the importance of data on decision-support systems. Bibri et al. [101] applied big data techniques to support better informed decisions in the so-called eco-districts, evolving to net zero energy districts (NZED) [105]. Both studies had a common objective, which was focused on the improvement of the energy efficiency in buildings and districts. A similar conclusion was extracted by Myeong et al. [106], who made use of long short-term memory deep NN to predict the air pollutants due to the buildings in urban areas.

Districts are not simply the interaction between buildings. It can also include other energy elements, such as the eV and charging stations [107], as reinforced by Luo et al. [28]. Park et al. [108] developed an artificial NN to merge the physical and virtual assets of a smart energy district where renewable, smart charging, storage and demand are integrated. Highlighting the sector coupling [99], balancing thermal and electricity loads, to satisfy the users' requirements. Calise et al. [107] developed an evolutionary algorithm to properly manage the storage elements in a sector-coupling problem. The authors proposed two operation strategies, for winter and summer, showing promising results (simulated, based on TRNSYS), where a district storage system contributes to the self-consumed electricity for more than 13%. Zhou et al. [109] proposed a stochastic MPC to minimize the cost for energy consumption of thermal regulation and eV charging. A similar approach was followed by Roccotelli et al. [110], who developed a stochastic mathematical model to balance the energy shares in a district, combining buildings, renewable energy, storage and eV. The authors achieved a 25% of cost reduction (peak shaving).

The references analysed in this section are summarized in Table 6, which summarizes the technologies and application fields being treated in the district level management.

### *5.2. Smart grid integration and flexibility*

Smart grid can be defined as a set of transmission lines, substations and elements that make possible the electricity exchange from the power plants to the buildings and other end consumers (for instance, industries) [111]. Unlike thermal energy, this section focuses on two aspects: (a) demand-side management, where the appliances and other electricity loads are included; (b) grid-connected renewable systems, coupling mainly, PV (photovoltaics) and wind farms facilities with the grid and the buildings. Smart grid is a very wide research area, but, within this work, only the building-related works are included, leaving out researches such as electricity markets, microgrids or grid resilience, among others.

#### *5.2.1. Demand-side management*

Electricity accounts for 30%–40% of the energy consumption in buildings, specially enhanced during peak hours [112]. Demand-side management searches for targeting behavioural patterns of energy consumption at consumer side to boost grid flexibility [26,113]. Shiftable (e.g. washing machine) and non-shiftable (e.g. fridge) loads need to be identified and their consumption predicted. Bourhnane et al. [114] implemented an artificial NN to forecast energy consumption of diverse appliances (air-conditioning (AC), fridge, furnace and microwave) and systems in a building, with an error of 2% [114]. This low error rate

**Table 6**
District energy management systems.

| Literature | Application field | Technologies |
|---|---|---|
| Marinakis et al. [102] | Decision support tool | Big data and multi-regression |
| Luo et al. [91] | Decision support tool | Clustering and artificial NN |
| García-Fuentes et al. [8] | Decision support tool | Fuzzy logic |
| Ibaseta et al. [86] | Decision support tool | Data-driven |
| Bibri et al. [101] | Decision support tool | Big data |
| Myeong et al. [106] | Decision support tool | Long short-term memory deep NN |
| Saba et al. [103] | Ontological Solution for Energy Intelligent Management | Rule-based |
| Lumbreras et al. [104] | District heating load prediction | Clustering & multivariable regression |
| Calise et al. [107] | Smart energy district | Evolutionary algorithms |
| Park et al. [108] | Smart energy district | Artificial NN |
| Zhou et al. [109] | Smart energy district | Stochastic algorithms |
| Roccotelli et al. [110] | District energy balance | Stochastic algorithms |

is mainly owing to the high quality of the data (clean and complete online available data-set).

The power-shiftable loads or appliances (PSA) have gained interest due to the emergence of eV and distributed generation systems [65]. The use of the eVs as electrical storage, through V2G (vehicle-to-grid) or G2V (grid-to-vehicle) approaches, lays out new scenarios for demand-side management, where eVs are integrated as an additional element of the grid infrastructure [115]. Duman et al. [65] analysed the coupling of smart thermostats for air-conditioning systems with eV loads to determine the operational phases according to the demand and renewable generation. However, load shifting strategies have a drawback, which is the energy peak due to the recovery of the normal operation. In [116], a load response model was deployed on response of end-consumers demand, while a second step operated to address the mentioned energy payback effect. Härkonen et al. [66] studied these PSA at home level for the case of Kalasatama from the users' perspective, concluding that some loads cannot be shifted such as lighting or cooking.

Ahn et al. [117] developed a total building power prediction model based on a long short-term memory technique combined with the Fourier transform. A similar exercise was done by Baek et al. [118] in a commercial building. Wang et al. [119] developed a fuzzy-based demand-side management for lighting controller, achieving 78% of energy savings in combination with LED bulbs. But demand-side management requires the interaction with the end-consumer. First of all, the algorithm should not disturb the end-consumer. Secondly, household consumption profile is essential. Chadoulos et al. [120], through the use of users' apps, clustered, via k-means, households under same consumption profiles to apply the same recommendations. Users should be the core of the energy transformation and new people-powered business models are crucial. Decarbonization, digitalization and decentralization in the energy systems replace the traditional energy markets. Thanks to the integration of technologies such as AI or big data, peer-to-peer platforms, virtual power plants, energy trading or energy-as-a-service, among others, are feasible [121].

The implementation of the flexibility services requires data. Liu et al. [122] proposed a virtual container to create the digital twin based on real data. The presented architecture enabled the user-side communication and smart metering virtualization to enable the creation of machine-learning models.

Table 7 includes the demand-side management references being analysed. It contains the application field of the work, as well as the technologies and energy model according to Table 4.

#### 5.2.2. Grid-connected renewable generation

Photovoltaics (PV) and wind power are the most widely used facilities for renewable electricity generation. PV systems present the main challenge of the mismatch between generation and consumption when connected to the grid (which is the usual configuration) [123]. Renewable energy generation might produce fluctuation in the power network. To overcome this issue, many authors are working in the prediction of the demand and generation and, indeed, as presented by Luo et al. [28], energy generation is the most frequent keyword in the current state of the art. Several machine learning techniques are applied. For instance, Pawar et al. [123] made use of artificial NN, SVM and ensemble models. The authors demonstrated that Particle Swam Optimization (PSO) based SVM is the model with the highest performance in terms of MAE to predict energy generation and couple with the grid, under the assumptions of their study.

Yao et al. [124] researched about a machine-learning framework, based on regression, to adapt the grid according to the predicted PV and wind energy generation and coupled with the load demands. Alghamdi et al. [125] stated that Apache Spark is the best framework to manage the data for real-time and batch processing to foster grid coupling. In such an analysis, techniques such as neural network or regression were investigated for large scale load prediction. Moreover, the integration of energy storage elements increase the grid resilience, then, being capable of adapting demand in peak price periods [26].

Zhou et al. [126] presented building integrated photovoltaics (BIPVs) combined with phase change material (PCM) to enable flexible charging/discharging strategies based on the change of state of the material, implemented based on mathematical models. Maturo et al. [127] also combined PV with PCM, modelling the systems as RC in Matlab, showing optimal parameters for PCM design. Another research based on PCM is [128], which reduced energy demand in 13%. These results show coupling electrical generation and thermal storage to provide power-to-heat approaches. The approach by Amin et al. [129] established a simulated environment for electricity grid demand prediction to match demand and generation from PV using thermal storage. Their results show how up to 100% of PV penetration is feasible.

Renewable energy prediction and demand-side management allows to enhance energy system flexibility and reduce building energy consumption. O'Conell et al. [130] presented rule-based strategies to manage unexpected events translated into higher demand. Their proposal led to an increase of 37% of energy flexibility, during summer, when combining PV plus battery storage. Undoubtedly, renewable generation and grid-adaptation should be combined with demand-side management strategies, according to Al Dakheel et al. [26].

Table 8 summarizes the references about grid-connected renewable sources and buildings. Similar to previous tables, it remarks the application field, technologies and energy model from Table 4.

### 5.3. Integration of BIM in smart buildings

The application of technologies like AI and big data allow for a better energy management of smart buildings. Although still low, but progressive, the adoption of BIM, in combination with IoT, is enabling new ways to create a better information flow and to initiate a shift from silo solutions to a smart ecosystem [131]. BIM paves the way for a virtual framework, where ontological features (e.g. based on Industry Foundation Classes (IFC) [20]) can be exploited to harmonize the

**Table 7**
Demand-side management systems.

| Literature | Application field | Technologies | Model type |
|---|---|---|---|
| Bourhnane et al. [114] | Appliances energy forecast | artificial NN | Black box |
| Duman et al. [65] | V2G | Mathematical modelling | White box |
| Mohammadian et al. [115] | V2G | Data-driven | Black box |
| Chen et al. [116] | Demand-side management | Mathematical modelling | White box |
| Härkonen et al. [66] | Home automation | Rule-based | Black box |
| Al Dakheel et al. [26] | Flexibility & Demand response | Adaptive load control | Black box |
| Ahn et al. [117] | Power prediction | Long Short-Term Memory & Fourier transformation | Black box |
| Baek et al. [118] | Power prediction | Long Short-Term Memory with PCA | Black box |
| Wang et al. [119] | Lighting management | Fuzzy logic | Black box |
| Chadoulos et al. [120] | Household consumption profiling | k-means | Black box |
| Giehl et al. [121] | Smart grid people-powered markets | big data & AI | Black box (Digital twin) |
| Liu et al. [122] | Smart grid digital services container | Data-driven | Black box (Digital twin) |

**Table 8**
Grid-connected renewable generation.

| Literature | Application field | Technologies | Model type |
|---|---|---|---|
| Pawar et al. [123] | PV forecast | ANN, SVM and ensemble models | Black box |
| Yao et al. [124] | PV-grid coupling | Regression | Black box |
| Al Dakheel et al. [26] | PV plus storage | Adaptive load control | Black box |
| Zhou et al. [126] | BIPV | Mathematical model | White box |
| Maturo et al. [127] | BIPV | RC model | White box |
| Yang et al. [128] | BIPV | Mathematical model | White box |
| Amin et al. [129] | Electricity demand and generation | Mathematical model | Grey box (Physics of building) |
| O'Conell et al. [130] | Flexibility | Rule-based | Black box |
| Alghamdi et al. [125] | Power grid | NN and regression | Black box |

interaction with the physical environment for predicted management of energy in buildings [132]. While BIM makes possible to understand the spatial features of the building, energy-related data characterizes the real performance of the building [133,134].

BIM is the basis for the creation of the digital building twin [42,135] leading to the Construction 4.0 paradigm [136]. However, digital twins must be real-time connected to the physical assets [136] for allowing simulation, prediction, and optimization [42,137]. When integrating the human-interaction and supporting the bidirectional communication, the digital twin is transformed into a cyber–physical building (CPB) [138] as a branch of cyber–physical systems.

BIM-based management creates the link between real and virtual assets, such as the case by Zaballos et al. [139]. The authors created digital twin models for indoor environmental quality in a smart campus for each of the zones, increasing the accuracy of the predictions.

Smart building management cannot be only limited to the operational stage, but the entire building life cycle should be considered [140]. Since the design stage, BIM, as a collaborative framework, allows to manage the entire life cycle [59,141]. Coupry et al. [136] suggested the combination of BIM and augmented and virtual reality along with IoT data (i.e. extended reality) to detect any misalignment in the construction phase or defects during maintenance (i.e. inspection [142]). These defects could lead to lower energy performance, enabling the estimation of energy resource efficiency per building design, but also considering the construction materials [143], which is not feasible with traditional CAD (computer-aided design) tools.

Continuous commissioning is possible from planning/design to demolition by detecting discrepancies between the digital twin and the real building behaviour [136]. This is also thanks to the new paradigm of BIM 4D, 5D, 6D or 7D, which complements BIM with schedule, costs, sustainable assessment (i.e. life cycle assessment - LCA) and operation [59,144]. BIM-based methodologies reduce the time and costs concerning LCA analysis, including: (a) energy performance due to construction materials; (b) $CO_2$ emissions; (c) indoor lighting; (d) comfort; (e) waste management. In the case of renovation projects, the use of BIM reduces the energy costs in 6.34% [145] because it supports the creation of more accurate simulation models. BIM represents the static data from a building and sets the basis for the building as a service [141,146].

BIM itself is useful for stakeholders collaboration, as well as it provides information for energy demand estimation, facility management or LCA, among others [146]. IoT data is needed to represent the real and synchronous operation of the building, while data should be exchanged between physical and virtual assets to satisfy the requirements of a digital twin [135,147,148]. These digital twins facilitate the dynamic energy simulation capabilities, relating energy consumption and building characteristics, such as thermal resistance or mass [149]. Thanks to this, new building services arise [146], e.g. energy predictions combined with AI algorithms, decision-making tools or buildings data exchange.

Digital building twins, as synchronized with the real performance, allow to create data-driven business models, e.g., performance-based contracts [150]. The authors of [150] took advantage of a BIM-based digital twin to extract the energy performance of each thermal zone to encourage users to use resources efficiently. Nevertheless, it should be extended to the assessment certification community, such as EPC or other indicators for ranking buildings, where digital twins allow dynamic operational evaluation [151].

Table 9 summarizes the analysis of the integration of BIM in the smart building context, taking into account the references used in this section.

### 5.4. Digital twin based energy management of smart buildings

Digital twins, combined with AI algorithms, are helpful to implement decision-making tools and recommend actions [39,140], reaching up to 50% of energy consumption reduction [137]. According to Pan et al. [42], the use of AI in the construction sector provides functionalities such as visualization, modelling, simulation, analysis, prediction and optimization, translating into digitalization, automation, risk mitigation and high efficiency advantage.

Commonly, digital twins just consume data, but a bidirectional link between the real and virtual assets becomes necessary, which is known as a cyber–physical system (CPS) [152] or, in the smart building context, cyber–physical building (CPB) [141]. CPB also enables the

**Table 9**
Analysis of the integration of BIM in the smart building context.

| Literature | Application field | Building stage | Benefits of BIM |
|---|---|---|---|
| Zaballos et al. [139] | Indoor environmental quality (IEQ) | Operation | IEQ accuracy per zone |
| Panteli et al. [59] | BIM 4D/5D/6D/7D | Building life cycle | Improved collaboration during life cycle |
| Kaewunruen et al. [145] | BIM-based retrofitting | Renovation | Input for simulation |
| Coupry et al. [136] | Inspection of defects | Building life cycle | Overlaying BIM and extended reality to visually detect defects |
| Lei et al. [142] | Inspection of buildings | Building life cycle | Self-inspection by 3D virtualization |
| Klimant et al. [143] | Energy resource consumption | Building life cycle | Materials features |
| Deng et al. [146] | Digital building twin | Building life cycle | 3D model for the digital twin |
| Sepasgozar et al. [147] | Digital building twin | Building life cycle | 3D model for the digital twin |
| Agounzul et al. [149] | Digital building twin | Building life cycle | Building characteristics |
| Evangelou et al. [135] | Digital building twin | Building life cycle | 3D model for the digital twin and static data |
| De Wilde et al. [148] | Digital building twin | Building life cycle | 3D model and IoT data integration |
| Spudys et al. [151] | Energy performance | Building operation | Assets modelling |
| Hunhevicz et al. [150] | Servitization with performance-based contracts | Building life cycle | 3D model for the digital twin |
| Wildenauer et al. [141] | Building as a service | Building life cycle | BIM as core data |

interaction between the building and agents (e.g., inherent electrical loads, distribution system operator (DSO) and aggregators) [153]. Thus, it provides a multi-agent framework for cooperation, whereas intelligent agents outperforms ad-hoc implementations [154], e.g., the case of the power grid. Consumers, as active players of the new energy markets, should be capable of interacting with the multiple elements at smart home, which form a poly-structure [155]. In other words, the energy system composes a hierarchical structure governed by humans.

Although CPB are usually enabled by the integration of BIM, IoT and AI, other data-driven virtual representations of the building behaviour (i.e., without the use of BIM advantages) are present in the literature. This namely knowledge models move from reactive to proactive maintenance [136]. For instance, Saad et al. [156] used the mathematical formulation of the grid operation to set up the CBS of the microgrid and distributed energy resources. The goal of the authors was to increase the resilience of the grid, similar to [157], minimizing cyber-attacks in the electrical grid [158]. Predictive maintenance applications are also enhanced [143].

CPB are mostly deployed for enhanced and smart building energy management by the implementation of AI algorithms. For instance, reinforcement learning, and in particular, Q-learning [159], is supported by the CPB environment, overcoming the calculation limits of existing building equipment (i.e. controllers with limited computational capacity). Katalinic et al. [154] deployed a P2P multi-agent system, with a Markov decision process, to support decision makers decision through well-established KPIs.

CPB also enables the capabilities for energy assessment and benchmarking, for instance, to detect anomalous consumers or understand energy behaviours [160] or BIM-based simulation for expected energy consumption [140]. Segmentation techniques like k-means are usually deployed to enlighten new areas for energy efficiency. In contrast to traditional methods that rely on annual energy calculations, CPB provides more insights in real building performance as they include the capability of temporal segmentation (e.g. occupied and unoccupied periods) [160].

Cross-vector coupling addresses the integration of different energy vectors and infrastructures, in particular electricity, heat and gas, either on the supply side, e.g., through conversion of electricity to heat, or at the demand side, e.g. by using residual heat from power generation for district heating. Several studies show that sector coupling can contribute to lower the overall costs of the energy system. Due to the inherent complexity, O'Dwyer et al. [161] formulated a composition of multiple models, based on clustering techniques, which are coordinated to predict the demand and supply sides. Thus, the initial challenge is split into sub-problems or subsystems. For instance, the district heating network is one of them and the objective is to reduce the financial cost of operation.

eVs, through V2G and G2V technologies, represents a distributed electricity storage assets[162]. The use of CBS in the eV field enables V2G automation and smart charge control via techniques such as neural networks. By means of the digital twin of the battery management system, the use of batteries as a decentralized storage element can also be optimized [163].

The CPB represents the building scenario which makes co-simulation strategies straightforward [164], reducing such a tedious process [30]. Nevertheless, the full potential of CPS in the building sector is not well exploited. For example, Kong et al. [68] established a CPS scenario for the co-simulation of building strategies for optimization of HVAC systems, but not considering BIM as input. Tan et al. [165] combine computer vision for better lighting control.

Table 10 overviews the usage of cyber–physical buildings in the energy management context and the interaction with the users from the references used in this section.

### 5.5. Smart readiness indicator as smart building driver

SRI is pursued by the new European directives [6] and new certification standards [61] to achieve the sustainable development goals [3,4]. Three main aspects are the focus of SRI: buildings, occupants and interaction with the grid [166]. The SRI is split into nine domains: (i) heating; (ii) cooling; (iii) domestic hot water; (iv) ventilation; (v) lighting; (vi) dynamic building envelope; (vii) electricity; (viii) electric vehicle charging; (ix) monitoring and control, with seven impacts: (a) energy efficiency; (b) maintenance and fault prediction; (c) comfort; (d) convenience; (e) information to occupants; (f) health, well-being and accessibility; (g) energy flexibility and storage. Fig. 5 [167] shows the matrix with the domains and impacts that evaluate the score of this indicator. Additionally, each one of the domains already defines a set of smart services that could be existing in a building.

The calculation method sets a level of functionality (0 means no smart operation and 4 states the highest smart level) for each of the services applicable per domain. This level of functionality is weighted per impact (there is a default weighting schema that can be customized by the assessor), obtaining a matrix where the domain effect in the impact is calculated. According to this matrix and the weighting schema for the domain/impact marks, the final score can be obtained as a percentage (0–100) to conclude with the smartness level (the higher, the smarter).

Three methods for the calculation of the SRI are available: (A) Simplified method, which limits the catalogue of services per domain up to twenty seven, (B) Expert SRI assessment, with an extended list of services (fifty four), and (C) In-use smart building performance, which includes metering results [46,168]. Method A is only applicable to residential buildings and small tertiary buildings (i.e. less than five

**Table 10**
Analysis of the smart energy management through CPB.

| Literature | Application field | Energy field | Users interaction |
|---|---|---|---|
| Pan et al. [42] | Construction 4.0 | Thermal & electricity | No |
| Pan et al. [140] | Construction 4.0 | Thermal & electricity | No |
| Srikanth et al. [153] | Building management | Smart grid | Yes |
| Katalinic et al. [154] | Multi-agent smart operation | Power grid | Yes, decision makers |
| Shvedenko et al. [155] | Smart home | Thermal & electricity | Yes, consumers |
| Coupry et al. [136] | Pro-active maintenance | Thermal & electricity | No |
| Saad et al. [156] | Microgrid resilience | Electricity | No |
| Weerakkody et al. [157] | Microgrid resilience | Electricity | No |
| Lou et al. [158] | Microgrid resilience | Electricity | No |
| Hosseinloo et al. [159] | Energy management | Thermal & electricity | No |
| Francisco et al. [160] | Energy assessment | Electricity | No |
| O'Dwyer et al. [161] | Flexibility | Thermal & electricity | No |
| Rehman et al. [162] | eV demand | Electricity | No |
| Bhatti et al. [163] | eV demand | Electricity | No |
| Kong et al. [164] | Co-simulation | Thermal & electricity | No |
| Tan et al. [165] | Lighting control | Electricity | No |

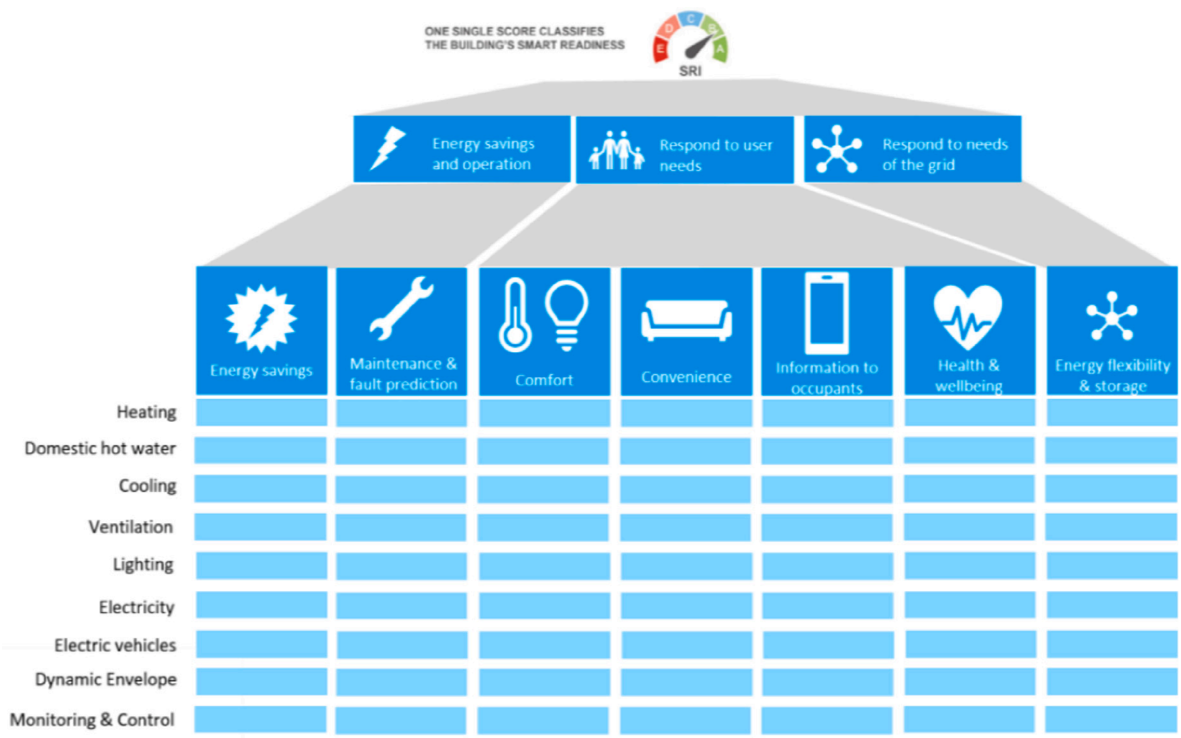


**Fig. 5.** Smart readiness indicator domains and impacts.
*Source:* [167].

hundred $m^2$), while method C requires, at least, one year of data, being method B the most commonly applied.

SRI is firstly used for smartness assessment of buildings. Vigna et al. [166] ran a triage evaluation methodology (three experts) for a single building in Italy, obtaining values between 55 and 66 out of 100. The reason for the difference can be explained by the interpretation of the functionalities per domain.

One of the main limitations of the SRI lies on the applicability in cold countries [169]. It does not recognize specific features of the buildings in such climates zones, specially stressed when district heating is used to supply heating and domestic hot water. The main reason is the lack of a characterization tool for thermal energy storage at building level (commonly used in cold countries combined with district heating generation systems). The SRI calculator only allows using of giant storage for the district heating itself [169]. Another limitation is its subjective nature, as pointed by Ramezani et al. [170]. The way of evaluating relies on experts who interpret the building features and, according to their experience, they establish weighting coefficients.

SRI helps decision-makers to select potential interventions (e.g. storage elements) or apply smart-ready services [46]. It requires the manual intervention from building's experts to determine the levels of functionality. To solve this issue, Markoska et al. [171] developed an automated tool to assess SRI. The authors relied on building metadata to be able to discover hardware equipment and software services so as to perform a Pareto analysis in the SRI score.

SRI is increasingly integrated in the energy management of buildings as it allows for the detection of more intelligent strategies for energy efficiency and comfort. For instance, Martínez et al. [172], throughout the measure–analyse–decide-act methodology, released prescriptive SRI analytics in an university campus, with a focus on the ventilation impact, with an overall value of 16.45 out of 100, and a low level of smartness. Gatt et al. [173] also used SRI to address nearly zero energy buildings (nZEB) in Malta, where energy generation and distribution are constrained due to its island character. The authors compared, by using simulation tools, the benefits of improved energy management solutions driven by the readiness indicator as for instance the integration of the dynamic building envelope domain.

Becchio et al. [174] simulated the improvement in terms of energy efficiency and SRI thanks of including smart-ready services in the dynamic envelope management domain (e.g. window slat with remote control). From the dynamic envelope rank of 19 out of 100 as baseline, the results showed that including shading control energy achieved values of 51 out of 100, including savings vary between 6.2% and 19.7% [174], depending on the functionality level. Fokaides et al. [175] ran a experiment in an university building in Cyprus, where an initial score of 52 showed relatively good smartness level. This analysis supported the definition in the field of renewable energy, which was not originally introduced in the building. Apostolopoulos et al. [168] compared methods A and B for retrofitting scenarios in Denmark, Czech Republic, Greece, Bulgaria and Austria. The main conclusion is that method B (expert method) provides lower impacts than method A (simplified method), although method B involves a more detailed analysis.

SRI is continuously evolving in terms of new services, changes in the domains and/or impacts; therefore, new versions of the calculation tool are being released. O'Connel et al. [130] assessed a flexibility indicator and how it could be included as input for future SRI developments. The same exercise was made by Marzinger at al. [176], but, in this case, focused on the quantitative load shifting potential of buildings. Within their approach, a re-definition of the SRI is proposed, where the activity coefficient is included (i.e. interaction of the buildings and thermal, electrical and gas grids). In this study, buildings moved from consumers to prosumers, anticipating external stimulus (e.g. weather conditions or users' needs) and included storage elements (in any of their variants) as key elements in the load shifting strategy. Similarly, Ozadowicz et al. [177] moved towards the use of SRI and BACS (building automation and control systems) defined in the standard EN-15232 for heating system and DHW (domestic hot water) temperature control, reaching up to 20% of energy savings.

Districts are not only an extrapolation of the individual SRI calculations, but also their activity should be considered. Marzinger at al., in a second study [178], proposed a methodology to extend the SRI focus from buildings to districts. Basically, the authors weighted the individual building SRI per energy demand. The authors demonstrated, in the city of Vienna, that only active interaction among buildings can contribute to load shifting [178]. Beyond districts, cities are being analysed to assess their smartness level, e.g., the research conducted by Zhao et al. [179]. The authors highlighted the importance of cross-sector approaches and multi-index criteria, where indexes like SRI are still far from being helpful. In this context, inter-criteria correlation methods are mostly used [179].

It should be remarked that one of the SRI domains refers to the information to occupants, including their feedback. Dell'Isola et al. [180] supported this domain by the joint disaggregation of electrical devices monitoring and customized user feedback, achieving savings between 22% and 27% thanks to better informed decisions of tenants.

When it comes to certifying buildings, energy performance certificates (EPCs) are consolidated assessment tools that express building parameters in the form of energy or environmental metrics [6]. Nevertheless, these are mainly steady-state [174], without considering human habits and dynamics of buildings.

The next generation of EPCs become the future to combine traditional techniques with SRI. According to Li et al. [60], an study realized in Belgium demonstrated that 50% of buyers took the EPC into account when buying the building. The integration of the SRI would give the EPC more accurate information, such as occupancy factors, behaviour, other data thanks to smart-ready services in charge of self-inspection (i.e. without needing an external assessor), as well as would impact in the EPC score thanks to the benefits of the building energy management systems (control algorithms are not considered in EPCs) [60].

EPC and SRI are not directly interconnected. For instance, Fokaides et al. [175], obtained relatively high values of SRI (52 out of 100 in a university building in Cyprus), which contrasts with relatively low values of EPC (label D for that case). The reason behind this is the fact that EPC does not consider smart services [181]. Koltsios et al. [181] expanded the EPC calculation rating by including SRI, LCA (life cycle assessment), LCC (life cycle cost) and human comfort. They proposed a dynamic way to calculate the EPCs by integrating IoT data, BIM (to extract building characteristics) and external sources (e.g. weather services).

Bisello et al. [182] analysed this new trend from the hedonic price perspective. That is, improving the energy efficiency and smartness of building in order to encourage people to invest in energy efficiency measures where the return of expenditures are sufficiently high. Their study in the city of Bolzano conducted price premium (relative price with respect to the current practices) on the residential market varies between 6.3% for label A label, 5.4% in case of B and 2.9% for C [182], even further increased with the SRI integrated. This work demonstrated the attractiveness of the new certification models for future building stock markets, either real state or end-consumers. This is the clear example of Malta, where nZEB (nearly zero energy buildings) are fostered according to the combined EPBD certification schemes plus SRI [173]. In fact, investors in the UK, Ireland, Germany and Denmark are ready to pay more when energy efficiency requirements are met [60].

However, one of the major concerns is the economic viability. Janhunen et al. [183] conducted an analysis based on cash flow. An investment of 6 M€ for PV plus battery and systems integration was made in a commercial building in Finland, reaching 91 out of 100 for SRI mark. The results demonstrated the attractiveness of this kind of investments, obtaining 10 years for payback period and 10% of return of investment (without subsidy from government) [183].

## 6. User empowerment technologies: Services for end-consumers

The main beneficiaries of the buildings are the end-consumers and/or owners [15]. According to the SmartBuilt4EU initiative (EU Smart Building Community) [16], a key aspect for success in smart buildings is the interaction between end-consumers and buildings. Buildings are weakly adapted to the multiple and diverse users' profiles [48]. Users have different comfort perceptions [48], but smart buildings should consider user preferences [70] in their operation.

Energy efficiency is not only the objective, but thermal comfort, satisfaction/well-being, lighting comfort or indoor air quality, among others, are also of paramount importance. Hence, homeowners should be able to interact with the facilities, such as setting their preferred initial set-point temperature, their preferred times of operation ranges for the thermostatic valves, hot water usage times, and preferred charging times of eV [65]. Nevertheless, as presented in Section 5.1, although the application of energy management strategies benefits the user comfort by establishing set-point temperature [68,69], many researches do not consider the user preferences. In this line, the AI is a driver to promote indirect energy savings through behavioural change [31], where the combination of algorithms with feedback from the end-users [184] makes understandable the consumers demand [185] and allowing users to use the energy facilities in a more efficient manner. Such an analysis was conducted by Hosseinihaghighi et al. [186] in households in Canada, where occupants behaviours were clustered obtaining differences of set-points for heating up to 5 °C.

Having said that, traditionally passive end consumers are turned into active market players with role of prosumers [65]. However, taking active participation means accessing building information and being aware of the energy use. As stressed by Dell'Isola et al. [180], users' awareness is crucial and it can be exploited by end-user applications. They provided detailed information on the energy use of the appliances, as well as benchmarking indices on expected consumption based on behavioural changes.


**Fig. 6.** Elements to be considered within the users' empowerment apps [84].

According to Daissaoui et al. [84], users' apps should be composed by sensor data and networks, as well as analytics with the support of big data techniques. Fig. 6 [84] depicts these key elements that make the users app attractive for the users' awareness. Additionally, the human subject-related factors should be taken into account [72]. This is the case of the analysis conducted in [120], where demand response programmes were integrated to adapt algorithms according to users' preferences. Both motivation, engagement and empowerment of users were achieved with gamification, information provision [187] and rewards. Gamification tools bring smart buildings closer to the end-users, i.e. they empower them.

Interaction with the users is also addressed with the CPB (cyber–physical building) approach, as stated before. Konstantakopoulos et at. [188] made use of the CPB approach to provide human-centric solutions. Through deep-learning methods (particularly long short term memory cells), the tool learned about the occupants' preferences and how these change according to manual control of assets. A point reward algorithm was also introduced to incentive energy-efficient use of the facilities [188], such as it is demonstrated with the air-conditioning and ceiling fans.

Even though the user's habits are usually repetitive, these can be modified due to unforeseeable situations (e.g. COVID-19), therefore, requiring adaptive algorithms. Occupancy information becomes necessary for the proper management of buildings [49]. Two types could be extracted [189]: spatial–temporal and behavioural properties. Solutions like occupants and resources location tracking [84] are able to obtain the presence, location and track of the end-consumers. Malatesta et al. [187] made use of k-means clustering to understand the occupants' routine and energy intensive periods along the year. Other studies make use of $CO_2$ sensors in combination with power consumption of the lighting system, indoor temperature and humidity to apply machine learning models, such as vertical Hoeffding tree (VHT) in [190], reaching up to 98.7% accuracy in the behavioural forecasting. WiFi connection techniques merged with artificial NN provide accurate methods to detect not only occupancy, but also counting people [191] to support the calculation of thermal loads. In this line, Amayri et al. [192,193] deployed interactive learning techniques to exchange information with the users so as to determine the number of occupants in an office building.

Numerous studies focus on users' empowerment, considering it a crucial aspect. However, there exists a noticeable gap in consensus between energy-efficient algorithms and user behaviour. While many energy management analyses prioritize optimizing energy savings, the connection with living spaces and user experiences is often overlooked. Initiatives like the European Bauhaus [194] advocate for user needs beyond functionality, emphasizing inclusiveness and harmony with nature, among other aspects. Methodologies such as co-creation, co-design, and co-development should thus be integrated into smart energy management. This leads to open research opportunities, as detailed in Section 7, including concepts like human cyber–physical systems or user-centric algorithms, with the objective of empowering consumers in the smart building management process.

## 7. Opportunities in smart buildings: Open research activities

Many advances have been made in the field of smart buildings. However, there are still other open research activities to continue approaching smarter buildings. This section describes the main opportunities that are envisioned. Three categories are considered: (1) smart energy management; (2) integration of BIM, digital twins and cyber–physical systems; (3) SRI and next generation EPCs.

### *7.1. Opportunities in smart energy management*

AI and big data techniques have provided many advances in the management of energy facilities in buildings. Indeed, they are increasing the energy savings, while ensuring comfort levels, thus, promoting more efficient building stock. Open research opportunities persist in this field, as summarized in Table 11, aligning with the challenges addressed in Section 3.1. Foremost, the importance of data efficiency and quality—crucial factors in training algorithms are emphasized. Two key opportunities have been identified: (a) enhancing data sample efficiency to ensure comprehensive datasets covering building thermodynamics (e.g., thermal inertia); (b) minimizing data noise, including biases and outliers. Both aspects aim to enhance the accuracy and resilience of algorithms [125], which are still exhibiting discrepancies compared to real building behaviour. Additionally, a novel trend in smart building contexts involves the integration of blockchain technology through smart contracts. This integration allows for pre-processing data and implementing data cleansing and redundancy algorithms [75]. This innovative approach showcases a promising avenue for further exploration.

Algorithms themselves present opportunities, particularly in terms of complexity. For example, ANNs often require a significant number of input controlling parameters [30], information not typically known by end-users. Additionally, these algorithms demand large datasets, leading to extended training times, rendering a plug & play AI-based controller for HVAC systems practically unfeasible [90]. Simplifying these algorithms has dual benefits—it enhances user awareness and participation while also facilitating replicability through plug & play capabilities.

Another crucial consideration is the enhancement of resilience – an integral domain within the SRI – aiming to amplify indirect energy savings [147] while concurrently enhancing comfort. Algorithms play a pivotal role in foreseeing and promoting the proactivity of buildings to bolster resilience. This is closely tied to the maximization of renewable energy sources to meet higher-than-expected energy demands, thus preventing energy wastage [16]. Algorithms are instrumental in aligning demand with consumption through the detection of demand and generation patterns.

Furthermore, the integration of additional data sources can enhance the functionalities of algorithms. An illustrative case is the incorporation of built-in building management systems (BMS) to support energy assessment tools and energy-efficient control mechanisms [175]. Another instance involves broadening the availability of connected assets and loads to optimize the management of multiple home and building energy systems [66], achieved through interoperability aspects [195].

**Table 11**
Research opportunities in smart energy management of buildings.

| Topic of research | Factors to address | Benefits | Challenges |
|---|---|---|---|
| Data efficiency and quality | Data sample efficiency and noise reduction | Higher accuracy | Low quality and insufficient amount of data |
| Data efficiency and quality | Data quality methodologies and cleansing | Improved trained algorithms | Low quality and insufficient amount of data |
| Algorithms complexity | Making them understandable for end-consumers | Users awareness and participation | Absence of significant customer awareness |
| Training periods | Time intensive and complex to deploy plug&play solutions | Replicability | Smart energy operation and maintenance |
| Resilience | Pro-activity of buildings to anticipate malfunctioning | Higher comfort | Smart energy operation and maintenance |
| Renewable maximization | Demand-consumption matching algorithms | Avoid waste energy | Smart energy operation and maintenance |
| Data integration | Built-in building management systems (BMS) | Enhanced functionalities | Low penetration of BIM methodologies |
| SRI-driven algorithms | SRI as trigger of the algorithms | Smarter buildings | Big data and AI to exploit the big amounts of data |
| User-centric algorithms | Algorithms addressing users' feeling (e.g., fuzzy) | Users as core | Absence of significant customer awareness |
| Decision-support tools | Extract value from data (i.e., key performance indicators) | Better informed decisions | Absence of significant customer awareness |

In conclusion, the development of SRI-driven algorithms, where SRI acts as a trigger for the control policy [46], is a pivotal aspect in promoting smarter buildings. Implementing SRI ensures the applicability of smart services across various domains, thereby enhancing the intelligent operation of buildings. SRI, by placing users at the core of building operation, necessitates the adaptation of user-centric algorithms (linked to the complexity aspects mentioned earlier) and addressing the uncertainties associated with human feelings. Methods such as fuzzy logic, which can handle the variability of comfort feelings [30], are underutilized. Additionally, decision-support tools should serve as the driving force for energy managers, employing big data and AI methods [147].

### 7.2. Opportunities in BIM-CPS integration

New policies regarding BIM allow for the integration of metadata in buildings to obtain characteristic of construction elements (such as materials, thermal zones, etc.). BIM also supports the creation of digital building twins, which integrated with IoT data encompasses cyber–physical buildings (CPB). Considering this perspective, opportunities in the utilization of BIM in smart buildings are outlined in Table 12. It is evident that one of the primary advantages of BIM is its contribution to decentralization and collaboration within the construction sector, facilitating self-assessment and self-operation of the building stock. The integration of CPB throughout the building life cycle fosters intelligent mechanisms for building management, leveraging novel paradigms such as the identification of thermal zones for the implementation of fine-grain control strategies.

Human-cyber–physical systems (HCPS) enhance the integration of CPS in building management through user feedback, contributing to improved comfort strategies [140]. Given that buildings are designed for occupants, ensuring comfortable conditions is paramount. HCPS facilitates algorithm adaptability, enhancing comfort across all zones and living spaces. Information derived from BIM provides localization of thermal areas and enables the amalgamation of diverse data in digital building twins [195], aiding in the identification of building areas for local control strategies. BIM models enrich algorithms with contextual information not typically present in time-series data used for training. This, in turn, contributes to the creation of well-informed environments for decision-making [106], streamlining the often tedious task of model calibration without a physical foundation [109].

Furthermore, the utilization of digital twin technology in civil engineering is still in its early stages. BIM holds significant potential to efficiently synchronize and store data continuously collected from IoT devices. Consequently, this technology can facilitate a synchronized interaction between physical and virtual entities for simulation [140], introducing novel approaches for grey models through the joint use of simulation tools with BIM [91]. These advancements pave the way for the next generation of digital twins, expanding the concept into multi-building interactions, such as districts. This evolution involves establishing communications between buildings and new interfaces with various data sources, including renewable sources [146].

### 7.3. Opportunities in the smart readiness indicator

The integration of the SRI indicator in the energy management and certification of buildings provides many benefits. First and foremost, attention is drawn to the next generation EPCs, which encompass both buildings and smart-ready services as defined in the standard EN-15232 [60]. A key advantage is the provision of a more reliable EPC, taking into account not only the energy demand but also factors such as heating set-points. This comprehensive approach enriches existing datasets with metadata and aligns with SRI certification schemes [60]. Table 13 succinctly summarizes the opportunities in this domain, outlining the benefits and mapping the challenges identified in Section 3.1.

The SRI also holds promise in the energy management of buildings. Applying more objective methodologies for the development of energy-efficient buildings throughout their lifespan is feasible [177]. The SRI methodology addresses the uncertainties associated with the current subjective nature of assessments [169], a concern that becomes especially pronounced when a custom approach is chosen over the default weighting method. Therefore, SRI serves as a reliable driver for seamlessly integrating self-assessment services.

In conclusion, the SRI methodology opens up new possibilities for demand response approaches by leveraging information from appliances (e.g., number of fridges, cookers, occupancy levels, etc.) [175]. By utilizing the services catalog provided by the calculation procedure, the next generation of services can be implemented to create smarter and, consequently, more efficient buildings.

**Table 12**
Research opportunities in BIM-CPS integration.

| Topic of research | Factors to address | Benefits | Challenges |
|---|---|---|---|
| BIM databases | Decentralization and collaboration in the construction sector | Better communication process | Low penetration of BIM methodologies |
| Human-CPS (HCPS) | Human behaviour and feedback integration | Improved comfort | Absence of significant customer awareness |
| Data integration | Model calibration needs reduction | Better accuracy | Low quality and insufficient amount of data |
| Digital building twins | Better informed environments | Improved decisions | Promotion of digital building twins |

**Table 13**
Research opportunities in smart readiness indicator.

| Topic of research | Factors to address | Benefits | Challenges |
|---|---|---|---|
| Next generation EPCs | Dynamics data integration in EPC with SRI | More accurate EPCs | Low quality and insufficient amount of data |
| SRI-driven algorithms | SRI as trigger for the energy management algorithms | Smarter buildings | Smart energy operation and maintenance |
| Self-assessment | SRI as smart indicator for buildings evaluation | New services | Smart energy operation and maintenance |

## 8. Conclusions

Smart buildings are a current trend in the scientific community, above all, thanks to the inclusion of technologies such as big data, IoT and AI in the life cycle of the building management. Many efforts have been placed in implementing more intelligent energy management strategies for higher energy savings and enhanced indoor comfort conditions. This study has reviewed the techniques that have been developed during the last two years to extract opportunities for upcoming researches according to the limitations that are currently detected in the state of the practice.

The construction sector is currently undergoing a digitalization process, in which new data comes into play. This is the case of BIM that represents the building features (e.g. materials, spaces, thermal zones...). BIM is the enabler for new concepts of digital building twins, where the combination of BIM plus IoT provides more evidences of building operation and maintenance patterns. Moreover, it enhances the management of the whole life cycle of the buildings, it supports the collaboration amongst stakeholders, and enables additional capabilities for energy management (such as grey models and co-simulation strategies).

The integration of BIM together with AI-based algorithms allows energy management systems to increase their accuracy compared to current techniques and methods. However, this implies an increase in data processing, which, coupled with the current complexity of the algorithms applied, makes training times unmanageable. At the same time, this complexity also leads to increased reluctance among final users due to non-understandable algorithms and the lack of interaction without the use of co-creation techniques. Scientific community should not forget buildings are for the occupants and their comfort. Techniques like fuzzy logic in new energy management strategies can be beneficial, as they enable to deal with the uncertainties and imprecise inputs associated to human factors such as users' feelings and preferences. All in all, the integration of new data from BIM, placing users the core of the smart building, and having better-informed decision-making tools would provide inhabitants with capabilities of determining current energy behaviour to adapt their needs.

In this survey, the new approaches, techniques and methodologies for the smart management of energy facilities have been analysed, including the sector coupling researches. Moreover, the integration of contextual data (such as BIM) and SRI-driven strategies have been discussed, where the clear impact of the SRI in the next generation of buildings has been identified. In this line, the benefits and advantages of the integration new data-sets (BIM, building logbooks, among other) and the proper use of the SRI methodology have been included. As the SRI is a European initiative, the focus of this review has centred on European countries. However, apart from this indicator, the conclusions drawn from the study can be extrapolated to non-European countries. The key findings reveal new directions that can be categorized into three levels: smart energy management strategies, integration of BIM/CPS, and SRI utilization. In terms of smart management, it is evident that data efficiency and quality pose challenges, resulting in prolonged training periods and less resilient algorithms. Addressing these limitations in the next generation of buildings requires the implementation of data quality methodologies for data cleaning. Additionally, current AI-based algorithms primarily focus on energy efficiency, often overlooking users' feedback and comfort enhancement. To overcome these shortcomings, simplification is necessary, complemented by new procedures to handle comfort uncertainties, such as the application of fuzzy logic.

In relation to BIM, this information serves as a valuable complement to the current time-series data utilized in the training processes. BIM facilitates the localization of sensors, thermal zones, and spaces within the building. This localization capability allows for the implementation of local algorithms that are not only more accurate but also simplify the complexities associated with large buildings. Moreover, it propels us into a new era of digital building twins, characterized by interactive and proactive buildings that create better-informed environments. This integration extends to human behaviour, streamlining the process for model calibration.

Last but not least, the SRI fosters innovative methodologies for building assessment and consequently introduces new services, particularly in terms of self-assessment. The utilization of SRI as a trigger for smart energy management algorithms, coupled with the services catalogue it provides, enables the creation of smarter buildings. Additionally, SRI contributes to the evolution of energy performance certificates (EPCs) from static to dynamic, incorporating real-time data for more accurate EPC certification. This dynamic approach not only enhances demand strategies but also provides a comprehensive understanding of the building's energy usage. SRI is still subjective and lacks of common, reliable and high-quality data for a proper analysis. Then, future trends should address the use of building data to determine new EPC plus SRI calculation methodologies in order to foster new regulations for smart buildings.

## CRediT authorship contribution statement

**José L. Hernández:** Conceptualization, Methodology, Investigation, Writing – original draft. **Ignacio de Miguel:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Fredy Vélez:** Writing – review & editing, Supervision. **Ali Vasallo:** Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jose L. Hernandez reports financial support was provided by European Commission. Fredy Velez reports financial support was provided by European Commission.

## Data availability

No data was used for the research described in the article.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL and ChatGPT in order to improve the grammar and readability of some sentences. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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