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Review

Energy Modelling and Analytics in the Built Environment—A Review of Their Role for Energy Transitions in the Construction Sector

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Abstract: Decarbonisation and efficiency goals set as a response to global warming issue require appropriate decision-making strategies to promote an effective and timely change in energy systems. Conceptualization of change is a relevant part of energy transitions research today, which aims at enabling radical shifts compatible with societal functions and market mechanisms. In this framework, construction sector can play a relevant role because of its energy and environmental impact. There is, however, the need to move from general instances to specific actions. Open data and open science, digitalization and building data interoperability, together with innovative business models could represent enabling factors to accelerate the process of change. For this reason, built environment research has to address the co-evolution of technologies and human behaviour and the analytical methods used for this purpose should be empirically grounded, transparent, scalable and consistent across different temporal/spatial scales of analysis. These features could potentially enable the emergence of "ecosystems" of applications that, in turn, could translate into projects, products and services for energy transitions in the built environment, proposing innovative business models that can stimulate market competitiveness. For these reasons, in this paper we organize our analysis according to three levels, from general concepts to specific issues. In the first level, we consider the role of building energy modelling at multiple scales. In the second level, we focus on harmonization of methods for energy performance analysis. Finally, in the third level, we consider emerging concepts such as energy flexibility and occupant-centric energy modelling, considering their relation to monitoring systems and automation. The goal of this research is to evaluate the current state of the art and identify key concepts that can encourage further research, addressing both human and technological factors that influence energy performance of buildings.

Keywords: energy transitions; energy modelling; energy analytics; data-driven methods; building performance analysis energy efficiency; energy flexibility; occupant-centric design; open energy data

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1. Introduction

In recent years, a notable research effort has been devoted to the conceptualisation of sustainability transitions [1] and, more specifically for energy, to the identification of "complementarities" at multiple levels [2,3]. Transition processes embody the necessity of radical-shifts and they represent an opportunity for innovation and entrepreneurship [4], with a clear focus on issues such as global warming and decarbonisation of energy systems [5]. In these innovation processes, the role of intermediaries and strategic niches appears to be crucial. In fact, understanding how actors can control and accelerate the energy transition is a key issue for research today [6] and intermediaries can play a fundamental role in this direction [7]. Intermediaries (i.e., public, non-profit, and private third-parties [8]) are actors which facilitate relations between key actors and enable knowledge sharing and pooling [9].The opportunities for the construction industry in this sense are relevant, because of the impact of built environment in terms of raw resources, energy and carbon emissions [10], but also because of the potential to exploit innovative technologies within emerging paradigms such as circular economy [11]. There is, however, the need to move from general instances to specific actions. These actions have to enable radical shifts compatible with societal functions and market mechanisms; for this reason, in this research we focus on energy modelling and analytics that can provide critical insights in this sense. At present, it possible to identify multiple enabling factors for radical shifts and acceleration of the process of change. First, the evolution of practices focused on concepts such as open data, open innovation, open science [12–14] and, in particular, open energy modelling principles [15,16]. Second, advances in building data interoperability (technical, informational and organizational) [17] and data availability at multiple levels, using technologies such as the Internet of Things (IoT) [18–20] and cyber-physical systems [21], which can enable, in turn, innovation in end-user energy delivery [22], and in energy infrastructures [23]. Third, the increasing decentralization of energy systems where the co-evolution of built environment and energy infrastructures [24] plays a fundamental role, that can be investigated by means of "soft-linking" of energy modelling approaches, from planning to operation [25]. Finally, innovative business models proposing concepts such as prosumer [26] and prosumager [27], which are determining changes in the way energy market works and energy trading takes place, for example using Peer-to-Peer automated exchange mechanisms, exploiting Blockchain technologies [28].

In this rapidly evolving framework, research aimed at radical changes in energy systems and built environment needs to consider the enabling factors reported above and to acknowledge the limitations and bottlenecks in view of energy efficiency and carbon reduction goals. The aim of this paper is to discuss to what extent and in what ways energy modelling and analytics can support the process of change for energy transitions in the construction sector. In Section 2 we illustrate the background of the research, explaining the fundamental elements that motivate it.

2. Background and Motivation

Energy transitions involve the transformation of the network of players and organisations traditionally working in the energy sector (e.g., policy-makers, regulators, transmission and distribution authorities, etc.) as well as the change of the role of customers, from passive to active (i.e., prosumers [26] and prosumagers [27]).In fact, socio-technical innovations are critically dependent on the possibility to access new information, knowledge and resources, which are key enablers for the development of innovative products and services [29], within a market mechanism. Construction sector can be conceptualized, for example, by considering three fundamental domains [30]: project, product and service. All these domains are going to be deeply influenced by socio-technical changes in energy transitions, which will transform the way buildings are designed, built and managed. Sharing knowledge among actors is crucial when addressing building energy performance in a comprehensive way, considering both human and technical factors [31]. In fact, the impact of occupants has to be considered from multiple stand-points [32] and users' behaviour can determine both "re-bound" [33] and "pre-bound" effects [34,35], that can create a substantial difference between expected and measured performance, which can be inscribed in the general category of "performance gaps" [36–38]. A "performance gap" can be found in all the stages of building life cycle [39] and the use of standardized assumption in modelling, e.g., to create Energy Performance Certificates, has to be critically questioned when using them to estimate actual energy consumption and potential savings [40].

Additionally, the dynamic interaction between building and energy infrastructures [41,42] has to be considered as well for multiple reasons (e.g., operational constraints, limitations of the penetration of renewables, innovative business model for the electricity market, etc.) and in light of possible developments in terms of "soft-linking" of energy models [25].

Finally, considering building performance from a whole life cycle perspective (indeed critical for emerging paradigms such as circular economy [11]), embodied energy in materials, technologies and processes represents another potential "performance gap" to be considered [43,44]. In fact, all these potential gaps create risks and lack of credibility when investing in energy efficiency and sustainability measures. Therefore, monitoring, verifying and tracking performance (i.e., energy, emission and cost in particular) using robust, transparent and empirically grounded methods is essential to evaluate the effectiveness of measures and share knowledge regarding practices. This, in turn, can contribute to investment de-risking and stimulate the growth of business "ecosystems" in energy and sustainability transitions, particularly for the construction sector. Additionally, the co-benefits of energy efficiency measures (e.g., improved indoor environmental quality, health, productivity, pollution reduction, etc.) [45] have to be considered both by policy makers and investors, to weight properly cost and benefits. Following the general trend towards open science, briefly outlined in Section 1, the research community in the energy field has stressed in recent years the fundamental importance of open energy data and models [46,47] and we can envisage an evolution towards systems of model [48] designed to address key problems in energy transitions, eventually taking advantage of "soft-linking" approaches [25,49]. Rather than being designed for separate applications, models can be potentially conceived and work like "ecosystems" [48] of interconnected applications, based on open data and modelling standard [46] where the researchers are opening their modelling "black-boxes" [47]. Indeed, transparent and robust models can become part of innovative business strategies, leading to techno-economically feasible pathways in transitions(thereby enabling a radical change to happen in practice). In fact, this review is part of a more extensive research work focused on "Buildings-as-Energy-Service" concept, in which separate literature reviews were conducted to explore both social and physical science perspectives on this topic. The concepts emerging from the reviews represent the basic elements of a Cognitive Mapping [50] process. The aim of this process is to create an inter-disciplinary research environment (a cognitive framework) [51] that is essential for innovation processes, where creativity is stimulated by the participation of user in the process of knowledge creation and sharing [52]. In Section 3 we describe the research methodology used to identify the role of energy modelling and analytical techniques in relation to the issues mentioned above.

3. Research Methodology

Considering the issues briefly outlined in Sections 1 and 2, the objective of this review study is to identify and analyse the features of energy modelling and analytical techniques that could be enabling factors in energy transition processes. The two fundamental research questions posed in this study are the following. First, what are the modelling techniques that can meet the criteria that will be described later in this section? Second, what are the essential characteristics (of modelling approaches) that can contribute to reduce the level of fragmentation of knowledge? The modelling framework proposed as outcome of the research attempts to reduce the level of fragmentation of the highly diversified body of knowledge available and to help in the conceptualization of processes of change (energy transition) by identifying opportunities, together with limitations and bottlenecks.

In this research both qualitative and quantitative data are analysed and it is therefore a "mixed approach" [53]. For this reason, we used concepts from Grounded Theory [54] as a reference for our research, in which both qualitative and quantitative data are utilised ("all is data" [55]). In brief, Grounded Theory (GT) can be defined as a "a set of integrated conceptual hypotheses systematically generated to produce an inductive theory about a substantive area" [56] and as "theory that was derived from data, systematically gathered and analysed through the research process" [57]. The results of a GT study are "a set of concepts, related to each other in an interrelated whole" [58].

The limitations of such approach depend on the fact that the selection in literature sampling depend on the subjective judgment (point of view) of the researcher and cannot stand outside of it [58]. However, the process can become more transparent and reproducible by stating the steps and the criteria used in it. In this research, we followed seven steps:

(1) Definition of knowledge domains of interest;
(2) Stratified search using domain and keywords in Web of Science database (WoS);
(3) Initial selection of pertinent literature on WoS;
(4) Definition of additional criteria for inclusion/exclusion of literature;
(5) Initial verification of literature using title, keywords and abstract;
(6) Final selection of literature;
(7) Detailed analysis of literature.

The fundamental knowledge domain of interest is "Building Energy Performance" (step 1) and the keywords considered initially are "Building stock", "Uncertainty" and "Flexibility" (step 2), to address fundamental topics in research. "Building stock" is chosen to identify examples of building energy modelling at multiple scales (e.g., for planning and policy, utility scale studies, etc.). "Uncertainty" is chosen to identify studies that analyse the critical dimension of energy performance uncertainty, which may create risks and lack of credibility for efficiency practices, starting from fundamental principles in Measurement and Verification (M&V) and Monitoring & Targeting (M&T). "Flexibility" is chosen to identify research regarding the interaction between building and infrastructures, which is strictly related to their technological co-evolution. The results obtained in step 2 are summarized in Table 1.

Table 1. Knowledge domain, keywords and criteria for literature selection.

Domain of Interest	Domain and Keywords	Sources in WoS Database	Sources in Categories: Architecture Construction Planning	Motivation for Criteria Selection	Source in Final Selection
"Building Energy Performance"	"Building Energy Performance" AND "Building stock"	1335	870	Building energy modelling for energy planning and policy targets, utility scale analysis, parametric building performance studies.	52
	"Building Energy Performance" AND "Uncertainty"	1551	705	Methods based on M&V and M&T principles that can help tracking energy performance transparently (and reducing uncertainty) and that can be applied at multiple temporal and spatial scales.	123
	"Building Energy Performance" AND "Flexibility"	1027	237	Strategies to control buildings and enhance their energy flexibility strategies in relation to energy demand in end-uses and user behaviour.	68

In order to obtain the final literature selection, additional criteria have been introduced and re-sampling of literature has been conducted iteratively until "theoretical saturation" was reached. Theoretical saturation term indicates "the phase of qualitative data analysis in which the researcher has continued sampling and analysing data until no new data appear and all concepts of the theory are well-developed and their linkages to other concepts are clearly described" [59].The criteria used in re-sampling have been summarized and motivated in Table 2. They are derived from previous research in the area of energy modelling [24,60] and consider the general trends towards the use of open data for energy research [46] and the necessity to increase of transparency in energy modelling [47]. In other words, the criteria introduced represent, in our opinion, limiting factors and constraints for the creation of "ecosystems" of models [48], which are briefly outlined in Section 2.

Table 2. Additional criteria introduced for energy modelling literature selection.

Criteria	Description	Motivation for Criteria Selection
Empirical Grounding	Based on empirical data, and tested on a relevant number of cases.	Reducing risk of investment in energy transitions and ensure the credibility of policies by means of evidence.
Harmonization	Methodologies in which redundancies and overlapping features are removed, ideally based on protocols and standard.	Avoid redundancy, multiplication of efforts and unnecessary increase of complexity of procedures. Streamline the implementation of models and procedures.
Scalability	Capability of analysing problems at multiple temporal and spatial scales.	Ability to work coherently and consistently on multiple temporal and spatial scales.
Interpretability	Ability to detect relevant cause-effect relationship, ideally combing statistical analysis techniques with physical understanding of phenomena.	Physical interpretation can help extract insights that are fundamental for the continuous improvements of processes and technologies.
Re-configurability	Able to be used in multiple stages of the building life-cycle, for example for design and operation, sharing similar underlying principles.	Creating a certain degree of continuity in the data analysis workflow during the life-cycle of projects.

In Section 4 the results of the review process are presented, structuring them according to three levels of analysis (related to the domain and keyword chosen, as explained before in this section) that correspond to the development, by means of iterative sampling, of the key concepts reported in Table 1. The overall research process is synthesized graphically in Figure 1.

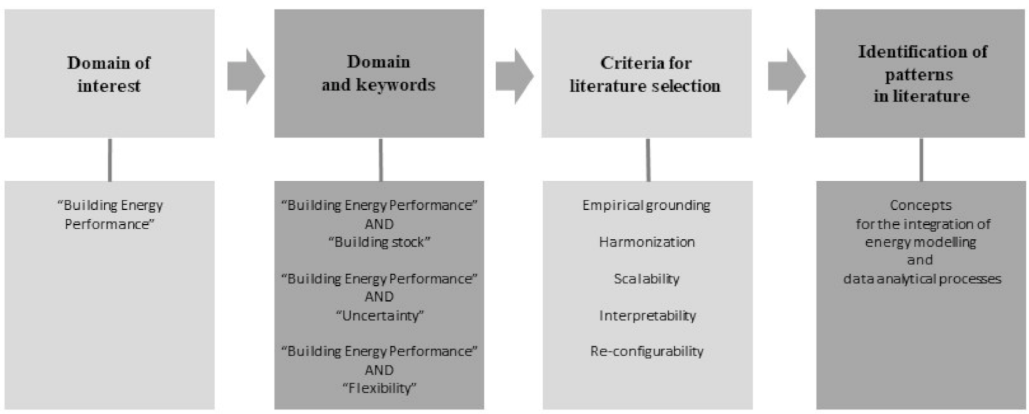

Figure 1. Diagram synthesizing the research process.

4. Results and Discussion

In this section we discuss how energy modelling and analytical tools could support energy transition processes for the construction industry, highlighting relevant insights for research across the three levels of analysis introduced in Section 3. The three levels proposed are indeed a strategy to perform a decomposition of the problem, going from general principles to specific issues that are emerging within the research framework. In Section 4.1 we analyse the topic of building energy performance analysis at multiple scales and its implications (e.g., in energy and planning policy, utility scale studies, etc.), which introduces the issues at general level (first level of analysis). In Section 4.2 we present harmonized methodologies (based on M&V principles and considering possible extensions) to analyse energy performance in buildings and we synthesize their characteristics (second level of analysis). Finally, in Section 4.3, we introduce innovative topics such as energy flexibility (infrastructures' interaction) and occupant-centric (users' interaction) energy modelling, which will contribute to redefine how buildings are actually designed and operated in the future (third level of analysis). Overall, throughout these three levels we show how many of the ongoing research developments are deeply related to the fundamental elements that motivate our research and are described in Section 2.

4.1. Building Energy Performance Analysis at Multiple Scales

Comprehensive reviews of building energy models have been published in recent years [61–63] and, while energy performance is particularly relevant, more comprehensive approaches to building performance analysis [64] are crucial for the evolution of the building sector. As anticipated, the analysis of building energy performance requires an understanding of both human and technical factors [31], and this confirms the inherent socio-technical dimension of energy modelling and analytics. It is therefore necessary to structure energy performance analysis with respect to both human and technical factors. In turn, this is important, for example, to address properly the gap between design and measured performance, i.e., the performance gap [36–38], introduced in Section 2. Further, the concept of statistical "Reference Buildings" [65] (RB) must be introduced to enable building performance benchmarking at multiple scales. RB models represent the common typologies, technologies and end-uses in the building stock, identified through statistical analysis and expert knowledge (e.g., on building technologies, types of end-uses, user behaviour, etc.) on a large-scale base. Building data are usually multi-level data, which makes it difficult to access the full information needed to describe in detail the performance of building stock. However, building energy modelling data can be organised in a hierarchical and standardized way; examples in this sense can be found at the EU level in the legislation on the definition of cost-optimal performance levels [66] and in EU Building Stock Observatory [67]. Further, in the US, technical standardisation has been tested with the definition of RB models [68,69], accounting also for the costs of various technological options [70].The role of energy modelling cycles and the importance of the level of detail (from conceptual to final design) are considered by the standard ASHRAE 209 [71]. Additionally, the use of hierarchical structures in datasets for building energy modelling can be found, for example, in performance gap studies [37], in the analysis of impact of automation systems [72], and in occupancy modelling [73].Further, with respect to building energy model calibration on measured data, we can find examples using multi-level data [74] and exploiting macro-parameters [75] (i.e., lumped quantities) to facilitate and guide the uncertainty and sensitivity analysis, together with the use of archetypes [76] (i.e., RB for a certain construction typology), and of additional information such as monitored internal temperature profiles [77].At the state of the art, multiple modelling options are available, depending on the scope of the analysis process, which range from physics based ("law driven") "white-box" models to statistics and machine leaning based ("data driven") "black-box" models. An analysis of the suitability of the different modelling strategies has been proposed by Koulamas et al. [78] and, more specifically for model calibration, by Manfren et al. [79]. Indeed, it is possible to use models to simulate performance (forward modelling) and to estimate model inputs from measured performance (inverse modelling) in multiple ways. Therefore, using forward and inverse modelling techniques [24] in a synergic way for calibration purposes is crucial. In this context, advanced techniques such as Bayesian analysis can help reconstructing built stock data under uncertainty [80–82], using probabilistic ranges for the model input parameters. The possibility to benchmark building performance on a large scale base [83,84] can increase the effectiveness of policies and can guarantee better decision-making processes, not only for policy makers but for multiple stakeholders (e.g., designers, energy managers, investors, etc.). In fact, the progressive convergence of bottom-up and top-down perspectives in energy modelling and planning for building stock [61] can contribute to the development of "soft-linking" approaches between various types of models [25] and, consequently, ensure consistency of actions in transition processes at multiple levels. Overall, a systematic statistical approach to building performance analysis [85] can be crucial to the evolution of design and operation paradigms for building stock. In recent years we assisted to an increasing commitment towards energy efficiency in buildings which led to the definition of paradigms such as Passive House [86], NZEB [87,88], and PEB [89], considering just the most relevant. Indeed, the possibility to deploy these paradigms at scale is subject to technical and economic constraints. In this sense, the use of statistical "Reference Buildings" can support techno-economic optimization studies [65,90], utility scale analysis of design [91] and operation of buildings [92] and energy planning at national scale [68–70], where innovative building paradigms are proposed and implemented. In terms of computation, the necessity of performing parametric (or probabilistic) simulation studies [93–95] is emerging and the algorithmic definition of simplified building models [96–98] can be exploited for building stock modelling at city scale [99–101] and regional scale [102]. In Table 3 we synthesize the outcomes of literature analysis regarding building energy performance analysis at multiple scales, highlight the main target of the different studies and their scale of analysis, namely national, regional, urban and stock. The latter indicates, in general, studies that are proposing building performance analysis on multiple typologies and end-uses.

Table 3. Building energy performance analysis—Target and spatial scale of analysis.

Source	Year	Target of Analysis			Spatial Scale of Analysis			
		Energy Planning and Policy	Utility Level Study	Parametric Building Analysis	National	Regional	Urban	Stock
Deru et al. [68]	2011	✔			✔			
Thornton et al. [70]	2011	✔			✔			
Goel et al. [69]	2011	✔			✔			
Ballarini et al. [102]	2017	✔				✔		
Delmastro et al. [99]	2016	✔					✔	
Ghiassi et al. [100]	2017	✔					✔	
Delmastro et al. [101]	2020	✔					✔	
Goel et al. [91]	2018		✔					✔
Meng et al. [92]	2017		✔					✔
Pernigotto et al. [96]	2014			✔				✔
Dogan et al. [97]	2016			✔				✔
Dogan et al. [98]	2016			✔				✔
Goel et al. [103]	2016			✔				✔
Badiei et al. [104]	2019			✔				✔

The examples reported before are clearly not exhaustive but they are used to illustrate the potential role of building energy performance analysis at large scale, using modelling methods that are transparent and reproducible, build upon (or compatible with) technical standardization. These topics are developed further in Section 4.2, consider two fundamental dimensions: the quantification of the impact of energy efficiency measures and the ability model dynamic behaviour (i.e., load profiles). Finally, at the beginning of this

Section we stressed the importance of a precise hierarchy for multi-level building energy modelling data. Another important aspect is that of "vertical integration" of information in energy modelling, from user up to infrastructures (e.g., user, individual spaces within the room, individual rooms, building zones, whole building, meter, energy infrastructure). Examples of research in this direction can be found in IEA Annexes on "Energy Flexibility in Buildings" [105] and "Occupant-Centric Building Design and Operation" [106]. These fundamental aspects of current research are discussed more in detail in Section 4.3.

4.2. Harmonizing Methodologies to Analyse Energy Performance

Appropriate spatial and temporal resolution of data is necessary to track building energy performance at multiple scales and energy metering data constitute, of course, the basic information layer. There is the need for harmonized methods that can ensure robust evidence (empirically grounded and validated) for efficiency measures (not only for research, but also for policy), by means of reliable statistics regarding the actual impact of efficient technologies [107,108] and especially by means of performance benchmarking of efficiency measures [109,110]. The term "harmonized" is used here to indicate, in general, methodologies in which redundancies and overlapping features are removed; harmonized methods can help documenting performance transparently, for example by tracking evidence of energy efficiency savings (and also related carbon and cost savings) in time and detecting the impact of influencing factors. Measurement and Verification (M&V) protocols [111,112] and methods represent the backbone in this sense and important research initiatives have been conducted in recent years to enhance and extend their applicability, such as the Uniform Methods Project (UMP) and other related projects [109,110,113]. The goal of these projects was harmonising the methods for the quantification of energy savings for different efficiency measures, both in residential and commercial buildings. Multiple measures (technologies) are included (HVAC, HP/chillers, CHP, lighting, envelope, variable-frequency drives, etc.). Another important project, focused on de-risking investment in energy efficiency, is the Investor Confidence Project (ICP) [114]. As already mentioned, the methods used in these projects represent an extension of the ones that can be found in M&V protocols [111,112] and technical standards [115–117], in which thresholds (expressed as statistical KPIs, representing the "goodness of fit") are given for the acceptability of models as calibrated [118] on measured data. Finally, open software is available [113,119,120] as a basis for further development that can potentially be enabled by open science principles (i.e., transparency and reproducibility of results, among others).

In general, these approaches are based on energy interval data (dependent variable) and weather data (independent variables) along with other independent variables (e.g., dummy variables for models of various occupancy and operational regimes) which can be derived from contextual knowledge and information. Instead of using energy data directly, it is possible to use the energy signature [115], which is the average power over the number of hours of operation in the interval considered. The most important independent variable for weather normalization of energy consumption is outdoor air temperature [121,122] and these methods are affine to variable-base degree days methods [92,123]. Temperature response methods are reviewed by Fazeli et al. [124]. Conceptual simplicity is one of their advantages (among others), compared to other meta-modelling techniques [125,126]. Automated model selection techniques [119,127] can be applied as well to compare the performance of multiple modelling options, using statistical KPIs representing their "goodness of fit". From an analytical perspective, it is important to be able to connect both the design and the operation phase analysis [128,129] in order to ensure consistency in the use of energy performance analysis techniques over the different phases of the life cycle [130]. In this way reliable limits for performance measured or estimated [131] can be produced and used against benchmarks, allowing a continuous improvement process (i.e., Plan Do Check Act is one of the key principles of Energy Management Systems [132]).

Far from being merely instruments for weather normalisation of energy use (i.e., outdoor temperature dependence), harmonised approaches can also help modelling dynamic loads (e.g., demand response) [109], ideally clustering operating conditions for typical profiles [133–135] to obtain specific insights on recurrent operating schedules (e.g., depending on the type of end-use).

In reality, understanding load dynamics at multiple scales is crucial for providing accurate estimates of the impact of flexibility measures that can inform policy [136] by creating a "soft link" between modelling approaches. Load modelling techniques can be used to complement "traditional" optimization approaches in cases where they are no longer sufficient and several operational configurations need to be studied [137]. Furthermore, the possibility of evaluating the thermal, electrical and fuel requirements with harmonised methods can extend further the principle of "soft-linking" of energy models in multi-commodity systems [138–142]. In this sense, harmonised methods should complement (in terms of general principles) open science-based approaches to energy research [16] because of their transparency. In addition, they may help to address related issues such as energy demand forecasts in future climate change scenarios [143–145] and definition of load profiles evolution due to efficiency measures and behavioural change, which are fundamental for optimizing decentralised energy systems in buildings [146] and communities [138,147,148].

In short, harmonised approaches can be used to discuss two main aspects of energy modelling research in a rigorous and transparent manner: the quantification of the effect of energy efficiency measures and the reconstruction of dynamic behaviour (i.e., time series modelling), such as load profiles analysis. Table 4 below provides a comparison of the main features of regression-based modelling methods that can meet the constraints set out in Section 3. We consider different types of end-uses, namely residential and non-residential, and different types of energy services, namely heating, cooling, domestic hot water (DHW), and appliances. First of all, the selected and reviewed literature reflects, in large part, empirically based studies in which the authors used operation phase data. The research is performed in all cases using regression-based (interpretable) methods that are significantly consistent with the harmonisation and standardisation principles outlined in this section. In terms of temporal scalability, the papers are categorised with respect to monthly, daily and hourly data. In certain cases, sub-hourly data are used, but we classify them as hourly data since this is the highest resolution considered by the model calibration thresholds proposed in the standards and protocols [118]; in any case, this resolution is adequate to capture the essence of building dynamic energy behaviour. In terms of spatial scalability, we consider building subsystems (building fabric and technological systems), building as a whole, building stock, and community and city scale. For the latter, the term design corresponds substantially to planning; the operational phase data are used as a basis for making accurate forecasts for the future. In addition, whole building energy balance is used in most situations, although in some cases (e.g., evaluation of building fabric characteristics) the energy balance at the zone or room level is used. Finally, with the term approximate physical approximation, we suggest the possibility of using regression coefficients to estimate physical quantities. Overall, the table illustrates how harmonized/standardized regression-based methods can cover several temporal and spatial scales of analysis and how they can theoretically combine design and operational phase performance analysis into the same analytical workflow (thereby satisfying re-configurability criteria, reported in Table 2). Finally, regression models can be used for both residential and non-residential end-uses to study energy services (heating, cooling, DHW, appliances) in multiple ways and can provide insights up to building system level when sub-metering data (e.g., thermal, electric) are available, while enabling, at the same time, the aggregation of results on a large scale base for building stock modelling.

Table 4. Harmonized regression-based modelling approaches for building performance analysis.

		End-Use		Energy Services				Temporal Scale			Spatial Scale					Interpretation	Phase	
Source	**Year**	**Residential**	**Non-residential**	**Heating**	**Cooling**	**DHW**	**Appliances**	**Monthly**	**Daily**	**Hourly**	**Building fabric**	**Technical systems**	**Whole building**	**Building stock**	**Community**	**Physical approximated**	**Design**	**Operation**
Lammers et al. [149]	2011		✔	✔		✔	✔	✔					✔					✔
Hallinan et al. [150]	2011		✔	✔		✔		✔					✔	✔	✔			✔
Hallinan et al. [151]	2011	✔		✔	✔	✔	✔	✔			✔	✔	✔	✔	✔	✔		✔
Danov et al. [152]	2011		✔	✔			✔		✔		✔		✔			✔		✔
Masuda and Claridge [153]	2012		✔	✔	✔		✔		✔		✔		✔			✔		✔
Bynum et al. [154]	2012		✔	✔	✔		✔		✔	✔		✔	✔			✔		✔
Masuda and Claridge [121]	2014		✔	✔	✔		✔		✔	✔		✔	✔	✔		✔		✔
Paulus et al. [127]	2015		✔	✔	✔	✔	✔		✔	✔		✔	✔					✔
Lin and Claridge [122]	2015		✔	✔	✔				✔			✔	✔			✔		✔
Hitchin and Knight [155]	2016		✔		✔				✔			✔	✔			✔		✔
Jalori and Reddy [156]	2015		✔	✔	✔	✔	✔	✔	✔	✔			✔					✔
Paulus [119]	2017	✔	✔	✔	✔	✔	✔	✔	✔	✔			✔					✔
Abushakra and Paulus [157]	2016		✔	✔	✔	✔	✔			✔			✔					✔
Bauwens and Roels [158]	2014	✔		✔					✔		✔					✔		✔
Erkoreka et al. [159]	2016		✔	✔			✔		✔	✔	✔					✔		✔
Giraldo-Soto et al. [160]	2018	✔	✔	✔			✔		✔	✔	✔					✔		✔
Uriarte et al. [161]	2019		✔	✔			✔		✔	✔	✔					✔		✔
Busato et al. [162]	2012	✔		✔				✔				✔	✔			✔	✔	✔
Busato et al. [163]	2013		✔	✔				✔		✔		✔	✔			✔	✔	✔
Krese et al. [164]	2018				✔		✔			✔			✔			✔		✔

Table 4. *Cont.*

Source	Year	End-Use		Energy Services				Temporal Scale			Spatial Scale					Interpretation	Phase	
		Residential	Non-residential	Heating	Cooling	DHW	Appliances	Monthly	Daily	Hourly	Building fabric	Technical systems	Whole building	Building stock	Community	Physical approximated	Design	Operation
Sjögren et al. [165]	2009	✔		✔	✔	✔	✔	✔	✔		✔	✔	✔			✔		✔
Vesterberg et al. [166]	2014	✔		✔	✔	✔	✔	✔	✔		✔	✔	✔			✔		✔
Meng and Mourshed [92]	2017		✔	✔					✔	✔			✔	✔		✔		✔
Meng et al. [167]	2020		✔	✔					✔	✔			✔	✔				✔
Oh et al. [168]	2020	✔		✔	✔	✔	✔			✔			✔	✔				✔
Westermann et al. [169]	2020	✔		✔		✔	✔			✔		✔	✔	✔				✔
Pasichnyi et al. [170]	2019	✔	✔	✔		✔				✔		✔	✔		✔	✔	✔	✔
Qomi et al. [171]	2016	✔		✔		✔		✔		✔	✔		✔		✔	✔	✔	✔
Afshari et al. [172]	2017	✔	✔		✔	✔	✔			✔			✔		✔		✔	✔
Afshari et al. [173]	2017	✔	✔		✔	✔	✔			✔	✔		✔		✔	✔	✔	✔
Allard et al. [129]	2018	✔			✔			✔	✔				✔			✔	✔	✔
Tronchin et al. [128]	2018	✔		✔	✔	✔	✔	✔		✔	✔	✔	✔				✔	✔
Manfren and Nastasi [131]	2020	✔		✔	✔	✔	✔	✔		✔	✔	✔	✔				✔	✔
Catalina et al. [174]	2008	✔		✔				✔		✔	✔		✔			✔	✔	
Hygh et al. [175]	2012		✔	✔	✔	✔	✔			✔	✔		✔				✔	
Asadi et al. [176]	2014		✔	✔	✔	✔	✔			✔	✔	✔	✔				✔	
Al Gharably et al. [177]	2016		✔	✔	✔	✔	✔			✔	✔		✔				✔	
Ipbüker et al. [178]	2016	✔		✔						✔	✔		✔				✔	
Goel et al. [103]	2016	✔	✔	✔	✔	✔	✔	✔		✔			✔	✔		✔	✔	

The possibility to employ advanced harmonized analytical techniques could, in principles, contribute to the development of innovative business models built upon Energy Performance Contracting (EPC) [179] principles, where dynamic operational conditions are clustered [134] and multiple regression models are combined together [156] to investigate performance, integrating data at multiple spatial and temporal resolutions, while retaining an approximated physical interpretation. Further, the graphical representation of regression-based methods can be combined with other visualization strategies used for energy (and exergy) flows at multiple scales, from building systems and sub-systems [180], to networks in multi-energy systems [181]. Physical-statistical (i.e., "grey-box") formulations [158,173,182–185], can extend the inherent capabilities of these modelling approaches even further and provide additional insights that may be particularly valuable in a continuous improvement logic, while retaining scalability [183,184].

Despite the variety of possible model formulations, we believe that data-driven approaches should use energy modelling definitions and quantities that are consistent with those proposed in the current technical standardization [186] to improve the comparability of results and consistency with policy objectives, for which standardisation plays a key role. For this reason, we report hereafter in Table 5 some experimental protocols (harmonized or standardized) with examples of applications at component level and building zone level. Indeed, the table highlights the potential continuity and integration of these experimental methods to estimate thermo-physical properties of building components and zones. Ideally, they could partially overlap with methods presented in Table 4, for example by alternating short-term measurement at higher frequency with long-term measurement at lower frequency [157] during building life cycle.

Table 5. Experimental protocols and applications.

		Type of Experimental Protocol				Application		Data Acquisition	
Source	**Year**	**ISO 9869**	**Co-heating**	**QUB**	**ISABELE**	**Component**	**Zone**	**Time Interval**	**Length of Data Acquisition**
Francis et al. [187]	2015	✔				✔		Subhourly	72 h
Rasooli and Itard [188]	2018	✔				✔		Subhourly	72 h
Erkoreka et al. [159]	2016	✔					✔	Subhourly	72 h, multiple periods
Uriarte et al. [161]	2019	✔					✔	Subhourly	72 h multiple periods
Bauwens et al. [158]	2014		✔				✔	Daily	2/3 weeks
Jack et al. [107]	2017		✔				✔	Daily	2/3 weeks
Alzetto et al. [189]	2018			✔		✔		Subhourly	1 night
Meulemans [190]	2018			✔		✔		Subhourly	1 night
Ahmad et al. [191]	2019			✔		✔		Subhourly	1 night
Rémi et al. [192]	2014				✔		✔	Subhourly	5–15 days
Thébault et al. [193]	2018				✔		✔	Subhourly	4 days

In QUB and ISABELE methods, the definitions used are in line with current technical standardisation; the physical parameters are represented by lumped quantities (thus reducing the number of parameters needed) and the model formulation greatly reduces the complexity compared to a physical "white-box" model, briefly recalled in Section 4.1. "White-box" models are detailed models based on physical laws used mainly for simulations during the design process and validated in accordance with energy simulation test standards [194,195].The potential contact point between "white-box" detailed modelling and "grey-box" (physical-statistical) lumped modelling parameters can be found in multi-level building energy model calibration [74] where "macro-parameters" (aggregated, lumped quantities) [75] are used to validate more detailed models, together with additional information such as internal temperature profiles [77] and other contextual information.

Indeed, the potential advantages of "grey-box" models are that they can be derived (and verified) from the basic concepts of energy analysis [196,197], built by using highly standardised rules [188], and they can employ efficient state-space [198] and analytical formulations [199]. Examples of validation of "grey-box" models using simulation test standards at the state of the art have been published by Lundström et al. [195] and Michalak [194,200]; a "grey-box" model for the detection of thermo-physical properties by inverse modelling has been implemented also in EnergyPlus, a detailed "white-box" modelling software [201]. Juricic et al. [202] considered the effect of natural weather variability in the identification of building envelope characteristics using these model types, showing how approximately two weeks of data are sufficient to achieve adequate accuracy. Finally, Baasch et al. [203] compared the performance of different "grey-box" methods in the derivation of thermo-physical properties from smart thermostat data acquisition (i.e., directly from temperature data instead of energy and temperature data), showing promising results.

"Grey-box" models can be also converted to "black-box" (i.e., statistical and machine learning models) for specific applications, for example control [204] or monitoring of internal conditions [205,206]."Black box" models are computationally efficient but they need to be trained on data before being deployed. As a result, "grey-box" models can be viewed as an intermediate stage between "white-box" and "black-box" models, and many examples of implementations have been found in recent years, ranging from experimental test facilities for building technologies [207] and construction components [208], to incorporation into the Building Information Modeling (BIM) workflow [209], and even to integrated room automation [210].

In addition, regression-based and "grey-box" model capabilities can be used in the Bayesian analysis framework. Bayesian analysis is suitable, for example, to 'reconstruct' building data (by estimating its characteristics) under uncertainty [80–82] or to evaluate the robustness of "grey-box" model estimates with respect to variable operating conditions [211] using Monte Carlo simulation methods [212], to reproduce realistically uncertain operating conditions.

What appears to be important for future research in this area is to increase the transparency of the modelling process by means of harmonised methodologies (using uniform rules and interpretable models as shown above) in order to verify and monitor output efficiently and to boost their level of automation without increasing complexity unnecessarily. Furthermore, the role of building automation [72,213] and monitoring systems [214,215] is crucial to understand the real dynamic behaviour of buildings by means of detailed data that can of course, complement energy metering, which represents the basic level of knowledge. Surrogate physical-statistical models (i.e., "grey-box" models) can be implemented also as "digital twins" (i.e., digital reproductions of the dynamic behaviour of their physical counterparts) at the level of construction technologies [216,217]. As a conclusion, in this Section we highlighted how harmonized methods for energy performance analysis are essential from multiple stand-points and how statistical and physical-statistical approaches are crucial for the evolution of energy research in buildings. Indeed, the methods reported and discussed in this Section can complement research on energy demand in end-uses based on epidemiology concept [218,219], providing however robust evidence on the performance of technologies and systems using empirically grounded methods, based on M&V principles.

4.3. Energy Flexibility and Occupant-Centric Energy Modelling

Energy flexibility in buildings [105] and occupant-centric energy modelling [106] for building design and operation are important research topics at present and they are directly addressing changes in fundamentals components of energy systems, such as users and energy infrastructures. Therefore, the topics discussed in this Section are complementing the ones in Section 4.1, focused on the potential of building performance analysis at scale, and Section 4.2, focused on harmonised methods for energy performance analysis (static and dynamic), showing how innovative concepts can contribute to reshape building design and operation strategies in the future. The analysis of the "mismatch" between building load profiles and on-site generation profiles (e.g., using PV power generation) has received a great deal of attention in recent years [41], due to the necessity of managing electric grid with increasing penetration of renewables. In this context, the concept of energy flexibility has been introduced to account for the dynamic interaction between end-user and electric infrastructures. Energy flexibility can be defined as the ability to control demand and supply according to consumer needs, grid conditions and climate [220]; an extensive review on this concept has been written by Reynders et al. [42]. There exist multiple options for increasing flexibility at the energy system level [136] and "soft-linking" of modelling approaches is increasingly important for energy planning and operation purpose [25,137]. More specifically, flexibility in buildings depends on the ability to use storage resources and to act on devices (including HVAC) after a trigger (e.g., time, power, energy price, etc.). Heating Ventilation and Air Conditioning (HVAC)systems are crucial because of their impact on the overall consumption of buildings and because of the potentially active role in energy infrastructure for demand response [221] and for absorbing surplus of energy from renewables [222]. From a technical perspective, energy flexibility in buildings can be exploited to shape building load profiles or to maximize the amount of energy that is self-consumed on-site [223,224], thereby increasing the matching between demand and on-site generation. The flexibility potential can be determined by the thermal inertia of building construction components (thermal mass) and by the presence of technical systems with storage (thermal and/or electric). Indeed, the exploitation of on-site renewables in buildings requires the adoption of technologies such as photovoltaics, heat pumps and energy storage [225]. Further, on the infrastructure side, flexibility requires an evolution of standardization of communication protocols to ensure efficient operation [226] and the results in this sense can determine a relevant change for the electric energy system as a whole [227], which may be combined with (and pushed forward by) consumer centric innovations in business models [228]. Specific KPIs [229] are required to describe flexibility potential and a large part of research at the state of the art concentrates on strategies to unlock it by means of control strategies [229,230], considering also related topics such as appropriate levels of modelling complexity and effort for their implementation [231]. In Table 6 we report an analysis of control strategies aimed at building flexibility for different end-uses and services using the same abbreviations as in Table 4. In Table 6 we consider the control objective in relation to flexibility, namely Load Shaping (LS) and On-site Renewable Maximization (ORM), following the arguments reported above. Additionally, the control types considered are Rule-Base Control (RBC), Optimal Control (OC) and Model Predictive Control (MPC). In Rule-Base Control rules are designed to fulfil a certain control objective but are not designed to achieve optimization of the overall system behaviour. In Optimal Control the control strategy is defined as an objective function to be optimized but doesn't include a prediction for the future. In Model Predictive Control the strategy is defined by means of an optimization performed with a certain control horizon (usually 24/48h); a comprehensive review on MPC has been written by Drgona et al. [232]. Further, we indicate the technical elements on which control strategies are focused. Also in this case, control strategies can be used for both residential and non-residential buildings a can exploit flexibility of heating, cooling and DHW demand by using the thermal storage capabilities of building fabric and technical system (e.g., water storage tanks). What appears to be fundamental, both in predictive and non-predictive cases, is the definition of dynamic operating schedules and set-points trajectories that are constrained by comfort requirements for heating and cooling services. However, the implementation of a detailed comfort model is challenging, due to the characteristics of control-oriented modelling approaches, and, for this reason, simplifications are generally considered when defining operational boundaries (i.e., the constraints for operation). Finally, the dynamic interaction with the grid is particularly important when dynamic tariffs are present and optimized control strategies have to consider the cost of imported and exported energy on a dynamic base.

Table 6. Control strategies aimed at building flexibility for different end-uses and services.

Source	Year	End-uses		Energy services				Control Objective	Control Type	Time Schedule	Set-points	Comfort Constraints	Load (Demand)	Production (On-Site)	Grid Connection (import/export)	Tariff
		Residential	Non-residential	Heating	Cooling	DHW	Appliances									
De Coninck et al. [233]	2014	✔				✔		LS, ORM	RBC	✔	✔				✔	
Klein et al. [234]	2015		✔	✔	✔			LS, ORM	RBC		✔		✔	✔		
Le Dréau and Heiselberg [235]	2016	✔		✔				LS	RBC		✔					✔
Dar et al. [236]	2014	✔		✔		✔		LS, ORM	RBC				✔	✔	✔	✔
Reynders et al. [237]	2015	✔		✔				LS	RBC		✔					
Turner et al. [238]	2015	✔			✔			LS	RBC	✔	✔	✔				
Esfehani et al. [239]	2016	✔		✔		✔		LS, ORM	RBC		✔		✔			
Alimohammadisagvand et al. [240]	2016	✔		✔		✔		LS	RBC		✔					✔
Salpakari and Lund [241]	2016	✔		✔		✔	✔	LS, ORM	RBC, OC		✔		✔	✔	✔	✔
Masy et al. [242]	2015	✔		✔		✔	✔	LS	RBC, OC	✔	✔					✔
Psimopoulos et al. [224]	2019	✔		✔		✔	✔	LS	RBC		✔	✔	✔	✔	✔	✔
Bee et al. [223]	2019	✔		✔	✔	✔		LS	RBC		✔		✔	✔	✔	✔
Oliveira Panão et al. [243]	2019	✔		✔				LS	RBC	✔	✔		✔			
Vivian et al. [244]	2020	✔		✔	✔			LS	RBC	✔	✔	✔	✔			
De Coninck and Helsen [245]	2016		✔	✔				LS	OC		✔	✔				✔
Halvgaard et al. [246]	2012	✔		✔				LS	MPC		✔	✔				✔
Maasoumy Haghighi [247]	2013		✔	✔	✔			LS	MPC		✔	✔	✔			
Corbin and Henze [248]	2017	✔		✔	✔	✔		LS	MPC		✔		✔	✔	✔	
Corbin and Henze [249]	2017	✔		✔	✔	✔		LS, ORM	MPC		✔		✔	✔	✔	
Lindelöf et al. [250]	2015	✔		✔				LS	MPC	✔	✔					
Garnier et al. [251]	2015		✔	✔	✔			LS	MPC	✔	✔	✔				
Kandler et al. [252]	2015	✔		✔				LS, ORM	MPC				✔	✔	✔	
Blum et al. [253]	2019	✔	✔	✔	✔			LS	MPC	✔	✔	✔				✔

It is worth noticing that there exists a potential methodological continuity between M&V practices at the state of the art, presented in Section 4.2, and innovative control strategies that represent an evolution of weather compensated control. This can be achieved, for example, using dynamic re-setting of heating and cooling curves [234] and machine learning algorithms whose performance can be tested and compared transparently in different weather conditions [250]. In general, by integrating regression modelling and clustering, it is possible to analyse variations of dynamic operational trajectories [134,156]. User behaviour has a huge impact on all the building services reported in Table 3 and, in recent years, an increasing research effort has been put on "Occupant-Centric Building Design and Operation" [106], as already mentioned before in the text.In particular, extensive reviews on this broad topic have been published recently [32], describing tools, methods and applications; more specific reviews have been dedicated to occupancy and behaviour modelling [254] and to occupant-centric control strategies [255]. The practical necessity to adapt modelling strategies in response to the purpose of the specific study (e.g., design, management, etc.) is indicated with the term "fit-for-purpose" [73]. Considering energy performance in a whole life cycle perspective, the variability of people behaviour and occupancy patterns has to be considered already at the early design stage, in particular in high efficiency and Nearly Zero Energy Buildings (NZEBs) [256]. After that, in the operation stage, occupancy can be measured in different ways [257] and data can be used to conduct realistic simulations [258]. In any case, as reported before, modelling occupancy patterns and user behaviour may require strategies that are customized (i.e., "fit-for-purpose") for the specific problem to be addressed: one possible solution is that of generating parametric or probabilistic occupancy profiles and modelling all the related variables (e.g., internal gains due to people and appliances, air change rates, etc.) in a transparent way [259,260]. This approach has been used, for example, to analyse building performance gap [261]. Realistic occupancy profiles are fundamental to address not only energy services but also to investigate related issues such as thermal comfort [262], Indoor Environmental Quality (IEQ) [263–265] and electric load profiles [266], among others.

As a conclusion, what appears to be important for future research in this area is increasing the transparency of the modelling process and linking it to harmonized methodologies (presented in Section 4.2) to verify and track performance efficiently without increasing unnecessarily the complexity of models themselves (i.e., maintaining an appropriate balance). Further, the role of building automation and monitoring systems is critical to understand the real dynamic behaviour of buildings. For example, data collected by monitoring systems [214,215] and/or automation systems [72,213] enable the performance characterization of envelope [160] and technical systems [267], together with occupancy patterns [257], already mentioned. Building performance monitoring and modelling can exploit also advances in IoT technologies [268] and open software [269], leading to innovative applications for energy and environmental management [270]. The possibility to rely on a combination of simulation methods and empirically grounded techniques for M&V can open interesting research opportunities in these areas.

4.4. Summary of Research Findings

In this section we describe the concepts emerging from studies that are in the intersections of the three levels of analysis presented in Sections 4.1–4.3, respectively. For this reason, we report in Table 7 the source, the level of analysis and the relevant concepts for the integration of energy modelling and data analytical processes. First, we can see how statistical reference buildings and parametric modelling represent the necessary basis for building energy modelling at multiple scales [80–82,103]. After that, "white-box" and "grey-box" modelling approaches can be integrated using a hierarchical multi-level approach [74] where "macro-parameters" [75] (aggregated, lumped quantities) are used as a mean to validated/calibrate more detailed model [80,118]. In turn, "grey-box" models based on regression and time series can guarantee empirically grounded "boundaries" for the estimation of building performance (providing harmonized methods) that may be used in multiple applications, while retaining a physical interpretation of the coefficients. The interpretability of models can provide multiple insights that can be exploited for the continuous improvement of technologies and practices (i.e., the PDCA approach [132]). Additionally, by combining regression, time series and clustering [134,156] it could possible to identify recurrent patterns in user behaviour [73,106] and in infrastructures' interaction [25,105,136], with a more precise quantification of the actual flexibility achievable. Both aspects (user behaviour and infrastructures' interaction) have to be considered in innovative business models for buildings where traditional Energy Performance Contracting is combined with innovative features [179] to ensure competitiveness and adequate level of services. Finally, data from automation and monitoring systems [72,160,213–215] are necessary to enable in depth analysis of performance, even though dynamic energy metering can be considered as the fundamental layer of information [214,215].

Table 7. Articles at the intersection of levels of analysis.

Source	Level	Year	Pattern Identified	Paper Title
Calleja Rodríguez et al. [75]	#1#2	2013	Reference building approach and parametric modelling	UK office buildings archetypal model as methodological approach in development of regression models for predicting building energy consumption from heating and cooling demands
Goel et al. [103]	#1#2	2016	Reference building approach and parametric modelling	Streamlining Building Efficiency Evaluation with DOE's Asset Score Preview
Zhao et al. [81]	#1#2	2016	Reference building approach and parametric modelling	Reconstructing building stock to replicate energy consumption data
Lim et al. [82]	#1#2	2017	Reference building approach and parametric modelling	Review on stochastic modeling methods for building stock energy prediction
Booth et al. [80]	#1#2	2013	Multi-level calibration	A hierarchical bayesian framework for calibrating micro-level models with macro-level data
Yang and Becerik-Gerber [74]	#1#2	2015	Multi-level calibration	A model calibration framework for simultaneous multi-level building energy simulation
Fabrizio et al. [118]	#2#3	2015	Multi-level calibration	Methodologies and advancements in the calibration of building energy models
Guyot et al. [77]	#1#2	2020	Multi-level calibration	Building energy model calibration: A detailed case study using sub-hourly measured data
Jalori et al. [134]	#2#3	2015	Regression-based approaches at multiple temporal and spatial scale of analysis	A new clustering method to identify outliers and diurnal schedules from building energy interval data
Jalori et al. [156]	#2#3	2015	Regression-based approaches at multiple temporal and spatial scale of analysis	A unified inverse modeling framework for whole-building energy interval data: Daily and hourly baseline modeling and short-term load forecasting
Ligier et al. [179]	#2#3	2017	Regression-based approaches at multiple temporal and spatial scale of analysis	Energy Performance Contracting Methodology Based upon Simulation and Measurement
Meng et al. [92]	#1#2	2017	Regression-based approaches at multiple temporal and spatial scale of analysis	Degree-day based non-domestic building energy analytics and modelling should use building and type specific base temperatures
Gaetani et al. [73]	#1#3	2016	User behavioural analysis	Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy
IEA-EBC [106]	#1#3	2017	User behavioural analysis	IEA EBC-Annex 79-Occupant-Centric Building Design and Operation
IEA-EBC [105]	#1#3	2014	Flexibility and dynamic interaction with infrastructures	EBC Annex 67 Energy Flexible Buildings
Lund et al. [136]	#1#3	2015	Flexibility and dynamic interaction with infrastructures	Review of energy system flexibility measures to enable high levels of variable renewable electricity
Dominkovic et al. [25]	#1#3	2020	Flexibility and dynamic interaction with infrastructures	Implementing flexibility into energy planning models: Soft-linking of a high-level energy planning model and a short-term operational model
Ahmad et al. [214]	#2#3	2016	Automation systems, measurements, sensors	Building energy metering and environmental monitoring—A state-of-the-art review and directions for future research
Aste et al. [72]	#1#2#3	2017	Automation systems, measurements, sensors	Building Automation and Control Systems and performance optimization: A framework for analysis
Carstens et al. [215]	#2#3	2018	Automation systems, measurements, sensors	Measurement uncertainty in energy monitoring: Present state of the art
Giraldo-Soto et al. [160]	#2#3	2018	Automation systems, measurements, sensors	Monitoring system analysis for evaluating a building's envelope energy performance through estimation of its heat loss coefficient
Serale et al. [213]	#2#3	2018	Automation systems, measurements, sensors	Model Predictive Control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities

As explained above, energy modelling and data analytical processes can be integrated in systems of models. Ideally, the creation of systems of standardized or harmonized "surrogate" physical-statistical models (i.e., "grey-box" models), which can be implemented in cyber-physical systems could represent a major breakthrough for energy modelling research. It can guarantee, for example, the possibility to act coherently at multiple levels in energy systems, using data analytics as a common background, and to create a certain degree continuity of performance analysis process during building life cycle, from design to operation phase. As discussed in Section 4.2, this result may be achieved by means of regression-based modelling approaches that combine conceptual simplicity and ease of implementation with adequate performance, in terms of analytics. In the next Section with indicate future research work that can be based on the outcomes of this research.

5. Further Work

Further research work could focus on knowledge mapping to enhance the integration and transparency of data within a modelling framework for energy in buildings, able to act at multiple levels. In Section 4.4 we described the points of contact between the multiple levels of analysis considered and we indicated how "surrogate" physical-statistical models (i.e., "grey-box" models that can be implemented in cyber-physical systems) could potentially work in "ecosystems" of applications. "Ecosystems" of models can address different types of end-uses (i.e., residential and non-residential), technological domains (i.e., heating, cooling, DHW, appliances) and applications (e.g., energy management, control, fault detection, environmental monitoring, etc.) while sharing a set of common underlying principles and rules. In this sense, surrogate models can act as "digital twins," that is to say digital reproductions of the dynamic behaviour of their physical counterparts (or systems). Harmonization and technical standardization play an essential role to avoid redundancy, multiplication of efforts and unnecessary increase of complexity of procedures. In fact, this could be the case of technical issues affecting multiple levels of information in the built environment, such as energy efficiency and flexibility or behavioural modelling and occupant-centric design and operation, described in Section 4.3. As mentioned in the introduction, building data interoperability [17] using common data exchange formats is necessary to increase the digitalisation and automation of buildings. The use of semantic web technologies [271] and standards based on IFC could support not only design but also operation (e.g., energy and environmental monitoring) [272], employing "surrogate" modelling strategies (physical/statistical, "grey-box") [209] compatible with the above mentioned principles. Finally, as introduced in Section 2, the research presented in this paper is part of a broader investigation, focused on the concept of "Buildings-as-Energy-Service": new forms of knowledge integration are needed to develop innovative services and products that can work as "ecosystems" and exploit this concept.

6. Conclusions

Energy transitions involve the transformation of the network of players and organisations that have traditionally worked in the energy sector along with new roles for customers. Radical innovation in the energy sector will have an impact on multiple domains in the construction sector (e.g., project, product and service). In this paper, we reviewed ongoing research on energy modelling and analytical tools that could support energy transition processes for the construction sector. In particular, we discussed how harmonised methods for analysing and tracking energy performance (Section 4.2) and innovative concepts such as flexibility and occupant-centric design and operation (Section 4.3) could contribute to a radical change in the built environment, using similar principles of analysis for actions that involve multiple scales (Section 4.1).The review process has been articulated according to three levels of analysis, introduced in Section 3 and reported in Section 4, ranging from general concepts to specific issues and we provided a summary of research findings as a set of interrelated concepts (Section 4.4). Overall, we identified criteria for energy modelling and analytical techniques (i.e., empirically grounding, scalability, harmonization, interpretability and re-configurability), that, in our opinion, constitute constraints to the creation of "ecosystems" of energy models aimed at supporting energy transition processes at multiple levels in the built environment. Regarding the first level of analysis (Section 4.1), systems of models can contribute to the creation of robust empirically grounded studies regarding efficiency for energy policy and utility scale actions. With respect to the second level (Section 4.2), they can be used to integrate data at multiple temporal and spatial scales, streamlining the analytical workflow (starting from consolidated M&V and M&T practices) and they can provide approximated physical interpretation of results, thereby increasing the transparency of modelling. Finally, in the third level (Section 4.3) they can help increasing energy flexibility in the interaction with infrastructures and improving the level of energy services in an occupant centric (design and operation) perspective. In all the levels considered in this review, we stressed the importance of studies that are empirically grounded and that can provide robust evidence for informing future research and policy.

As discussed in Section 5, these principles can constitute the basis for further research work, focused on developing specific applications built on top of them. In fact, the research proposed is part of a broader research activity focused on the "Buildings-as-Energy-Service" concept and the creation of a Tool Kit for knowledge integration regarding this topic, with the support of Cognitive Mapping technique. New forms of knowledge integration are needed to develop innovative services and products and this Tool Kit may be used to engage multiple users in the process of knowledge creation and sharing. Conceptualization is fundamental in innovation studies for energy and sustainability transitions but while general concepts can be clearly understood, what is still unclear is how these concepts can then translate into specific projects, products and services for energy transitions in the built environment, using innovative business models. Tools for knowledge integration can give a contribution in this sense.

Further, the problem of data accessibility has to be considered as well. The lack of detailed data or inadequate data reliability due to non-standardized collection procedures can be addressed using harmonized methodologies (described in Section 4.2). At present, this is causing a knowledge gap that undermines informed policy choices in the energy transition process (as well as in many other processes). Sensors, the Internet of Things (IoT), together with processes of automation and digitalisation described in this paper, could enable access to a greater amount of data for the building stock. In this context, it will be important to create open data repositories about technology, energy demand for end uses and weather data. Standardized and up-to-date data could enable transparent and consistent modelling processes at multiple scales of analysis, partially reducing the effort and stimulating the development of innovative energy technologies and services.

As a conclusion, in this paper we proposed a reflection on concepts that can help structuring future R&D activities and we highlighted a potential way to increase transparency, robustness and reproducibility in modelling by linking general principles emerging from the state of the art of research, to specific applications, employing harmonized methods as the core element. We believe that sharing information and making it more transparent and easily accessible can support multiple communities involved in R&Dfor energy transitions overcoming social and technical issues that may hinder the radical shifts that are necessary for long-term built environment sustainability.

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