Techno-economic analysis and energy modelling as a key enablers for smart energy services and technologies in buildings

Published Version:
Manfren, M., Nastasi, B., Tronchin, L., Groppi, D., Garcia, D.A. (2021). Techno-economic analysis and energy modelling as a key enablers for smart energy services and technologies in buildings. RENEWABLE & SUSTAINABLE ENERGY REVIEWS, 150, 1-14 [10.1016/j.rser.2021.111490].

Availability:
This version is available at: https://hdl.handle.net/11585/828661 since: 2021-07-23

Published:
DOI: http://doi.org/10.1016/j.rser.2021.111490

Techno-economic analysis and energy modelling as a key enablers for smart energy services and technologies in buildings

Massimiliano Manfren[*a], Benedetto Nastasi[b], Lamberto Tronchin[c], Daniele Groppi[d], Davide Astiaso Garcia[b]

[a] Faculty of Engineering and Physical Sciences, University of Southampton, Boldrewood Campus – SO16 7QF Southampton, United Kingdom

[b] Department of Planning, Design, Technology of Architecture, Sapienza University of Rome, Via Flaminia 72 – 00196 Rome, Italy

[c] Department of Architecture (DA), University of Bologna, Via Cavalcavia 61 47521, Cesena, Italy

[d] Department of Astronautical, Electrical and Energy Engineering (DIAEE), Sapienza University of Rome, Via Eudossiana, 18 – 00184 Rome, Italy

Abstract

Smart energy services and technologies are key components of energy transition and decarbonisation strategies for the built environment. On the one hand, the technical potential of the building stock in terms of energy, emissions and cost savings is large and exploited only partially at present. On the other hand, the increasing availability of data generated by smart meters, smart devices, sensors and building management systems can help monitoring, verifying and tracking building energy performance improvements in a transparent way. In particular, energy modelling and data analytics can provide empirically grounded and tested methods to standardize the way energy performance is measured and reported. Further, techno-economic analysis is crucial to ensure the feasibility of innovative business models. For these reasons, this paper aims to address the role of techno-economic analysis and energy modelling as key enablers for next-generation energy services and technologies. In terms of methods, scientific literature selection criteria are derived from previous research and are focused on limitations and bottlenecks to the achievement of innovative business models, which are motivated, at their very basics, by energy, emission and cost savings. Additionally, besides these potential savings, smart energy services and technologies can provide multiple additional benefits such as improved Indoor Environmental Quality (IEQ) and energy flexibility on the demand side, with respect to energy infrastructures. First, the research identifies the key elements that are necessary to integrate and to streamline techno-economic analysis and energy modelling processes. After that, it highlights potential advances in the broad area of energy transitions and decarbonisation of the built environment that can be achieved as an evolution of current practices and processes. Finally, it envisions the creation of "eco-systems" of interacting models for the building sector that share common underlying principles.

Keywords: Smart energy services; Smart energy technologies; Energy transition; Energy Performance Contracting; Measurement and Verification; Energy Analytics; Decarbonisation; Built Environment.

Highlights:

- Smart energy services and technologies as key components of energy transitions.

[*] Corresponding author:
Tel: +44 02380592869
e-mail: M.Manfren@soton.ac.uk

- Techno-economic analysis principles to ensure feasibility of innovative business models
- Necessity of empirically grounded and tested methods to analyse and track performance transparently.
- Possibility to enhance the capabilities of methods and models at the state of the art.
- Potential to create “eco-systems” of interacting models for the building sector.

1 Introduction

Smart energy services and technologies in buildings can contribute to a radical efficiency improvement, which is crucial for sustainability transitions that represent today a challenge involving changes both in science and society [1]. It is widely acknowledged that the reduction of the environmental impact of the construction sector and built environment is a crucial component of sustainability strategies and is part of the agenda of sustainability transition research [2]. Further, the co-evolution of research in built environment and energy sectors is an open issue, considering, for example, the dynamic interaction among buildings and energy infrastructures in a context of increasing decentralization. Planning and managining sustainability transitions requires conceptualizing and explaining how a radical change can take place while satisfying fundamental societal needs, for example by means of innovations in processes and practices, across different sectors. A possible conceptualisation of construction sector [3] proposes three fundamental domains: project, product and service. Each domain has different markets, companies, business models and regulation. One of the major goals of sustainability transitions research for the built environment is identifying the limitations and bottlenecks within these domains as well as at the interface between domains, that can compromise performance in different building life cycle phases. In fact, buildings are long-terms assets and addressing limitations and bottlenecks from a techno-economic perspective (using life cycle costing), is crucial to promote business models that consider the whole life-cycle and enable a long-term view. From the energy and environmental point of view, the use of methods such as life cycle assessment (LCA), while being crucial for innovative economic paradigms such as Circular Economy [4], is itself a critical issue in built environment research [5]. In fact, there are large variations in how the method is currently used in practice [6], making it difficult to use for transparent performance comparison and benchmarking. Clearly, this fact determines a problem of consistency and credibility of practices and policies. We can see how the potential gaps between simulated and measured operational energy and carbon emissions represent a debatable issue in which some researchers highlight the problem of energy modelling literacy [7], while others underline the importance of training and of understanding the use of complex simulation software as an analytical tool rather than a predictive one [8]. A similar performance gap problem appears with respect to embodied energy and carbon emissions [9], for the reasons quickly reported before (i.e. variations in the way LCA is applied in practice). For this reason, a particular effort has to be devoted to the identification of influential factors in LCA, in order to assess the robustness of results [10] with respect to uncertainty and variability in inputs. Despite the inherent difficulties, the technical potential of the building stock in terms of energy, emissions and cost savings is large and exploited only partially at present. Additionally, the increasing availability of data generated by smart meters, smart devices, sensors and building management systems can help monitoring, verifying and tracking building energy performance improvements (e.g. operational energy demand reduction) in a transparent way. In particular, energy data analytics can provide empirically grounded and tested methods to standardize the way energy performance is measured and reported, starting from consolidated practices in Measurement and Verification (M&V) field, which can evolve further to accomplish additional needs. Transparent and reliable energy performance assessment is crucial for the development of innovative energy services and technologies in buildings, which can contribute to the feasibility of sustainability transitions and decarbonisation paths for the building sector. The paper aims to discuss the role of techno-economic analysis and energy modelling as key enablers in this direction, identifying some of the critical aspects related to their implementation as part of innovative business models and summarizing essential features and insights that emerge from research in this broad area.

2 Background and motivation

Sustainability transitions research is moving rapidly from an emerging field [11], to a challenge involving the evolution of science and societal change [1], to an agenda for future initiatives [2], with the fundamental goal of accelerating transition processes. In brief, sustainability transition research focuses on the conceptualization and explanation of how radical shifts in socio-technical systems can occur in a way compatible with societal functions. This implies, clearly, considerations on how radical shifts can become feasible from a techno-economic perspective. This type of research focuses on the "meso"-level of socio-technical systems, thereby differentiating from "macro"-level (e.g. macro-level economic and environmental problems) and "micro-level" (e.g. individual choices and behaviour) research. The "meso"-level is essentially the regime that represents the dominating socio-technical patterns of interaction and learning processes. Sustainability transitions research addresses multiple sectors such as electricity, heat, built environment, agro-food, transportation, etc. For the research regarding energy sector, in particular, the term used is energy transitions and we can find examples of this kind of research addressing complementarities in energy systems [12] and energy policies [13]. There are also examples of application of this approach for the built environment [14]. In the past, several researchers in the fields of sociology of technology and evolutionary economics have stressed the importance of niches as drivers of innovation. Niches can work as protected (from market selection mechanisms) environments for the incubation of new ideas, where new socio-technical regimes can emerge and develop. Technological niches are particularly interesting for energy research, as they can represent spaces for experimenting the co-evolution of technology, user practices, and regulatory structures. Further, technological niches can be successfully linked to market niches by means of institutional learning processes [15]. Innovative energy services and technologies represent a substantial part of business models that could enable energy transitions and decarbonisation in practice, initially at the level of niches and then at large scale. However, radical shifts require a long-term view of problems while a short-term view is often considered from a business perspective. Nonetheless, appropriate financing mechanisms could, in principles, enable long-term investments, when successful business models are available. For this reason, Life Cycle Costing (LCC) methods have to be used in order to evaluate costs in a long-term perspective and multi-objective optimization (using Pareto frontier analysis) can be used to evaluate simultaneously energy and cost objectives, in order to find the best compromise solutions. Streamlining and making this process more transparent and robust (with respect to the inherent uncertainties) is an important goal for research. For this reason, the paper considers first techno-economic accounting methodologies and then techniques for energy modelling and analytics at the state of the art, because they represent (together) essential pre-requisites to ensure the feasibility of innovative services and technologies. Finally, the outcomes of analytical processes could enable multiple feedback loops and, consequently, contribute to the improvement of processes and technologies and the emergence of new business opportunities. In the next section, the methodological approach followed in this research is described in detail, highlighting the relevant steps and features considered for the selection of literature.

3 Methods

Considering the issues outlined in Section 1 and 2, the fundamental research question of this study is whether it is possible to create a knowledge framework, in the areas of techno-economic analysis and energy modelling of buildings, able to meet the criteria specified later in this section. The knowledge framework should attempt to reduce the level of fragmentation of the highly diversified body of knowledge available, thereby helping in the conceptualization of processes of change (achievable by means of innovative energy services and technologies) by identifying opportunities, together with limitations and bottlenecks. The research proposed combines qualitative and quantitative information and can be identified as a mixed approach [16]. For this reason, we consider in the research process concepts from Grounded Theory [17] as a reference, where we utilise both qualitative and quantitative data ("all is data" [18]), in order to orient our research. 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" [19] and as "theory that was derived from data, systematically gathered and analysed through the research process" [20]. The results of a GT study are communicated as "a set of concepts, related to each other in an interrelated whole" [21]. The limitations of such approach are in the fact that the resulting knowledge framework depends on the researchers' views and should be contextualized accordingly. Nonetheless, by expliciting the selection criteria for literature, as well as their relation to studies previously conducted, we can present the research process in a transparent and reproducible way. In fact, we pursued a purposive sampling strategy where sources of information are chosen based on the researchers' judgement in a non-probabilistic way. The selection of criteria is based on previous research conducted by the authors and aims to address fundamental limitations and bottlenecks previously identified. First, the problem of integrating energy efficiency measures, demand side management, on-site generation and energy storage technologies in the built environment [22]. After that, the role of open data and energy modelling standards in fostering multi-disciplinary research in the energy sector, from system planning, to design and operation [23]. Further, the possibility to link design and operational phase analysis (thereby enabling a whole life cycle analytical approach) using transparent and interpretable data-driven techniques (e.g. regression-based) [24]. Finally, the identification of key characteristics of energy modelling and data analytics that can contribute to the evolution of the construction sector at multiple levels [25]. In brief, this paper aims to synthesize the outcomes of previous research and analyse how they can be integrated within innovative business models for energy services and technologies. Therefore, fundamental criteria used for literature selection and their motivation, in relation to previous research, are summarized in Table 1.

Table 1: Criteria for literature selection

Criteria	Description	Motivation
Empirical grounding	Based on empirical data, and tested on a relevant number of cases.	Ensuring credibility with an evidence-based approach aimed at building trust in the solutions proposed.
Harmonization	Methodologies in which redundancies and overlapping features produced by different research groups are removed, ideally based on protocols and	Avoiding redundancy and multiplication of efforts, simplify and streamline implementation, ease the benchmarking process when validation cases are

	standards.	available.
Scalability	Capable of analysing problems at multiple temporal and spatial scales.	Enabling consistency and coherency in the use of analytics at different temporal and spatial scales of analysis.
Interpretability	Able to detect relevant cause-effect relationship, ideally combing statistical analysis techniques with physical understanding of phenomena.	Enhancing the possibility of harmonization and the extraction of useful insights by referring to physical quantities. Enabling multiple feedback loops for continuous improvement of processes and technologies.
Re-configurability	Able to be used in multiple stages of the building life-cycle, for example for design and operation, using the same underlying principles.	Creating a seamless integration in the data analysis workflows performed during different building life-cycle phases.

The analysis of the fundamental information contained in the selected literature and its codification has been performed incrementally and iteratively, using Table 1 criteria, until "theoretical saturation" was reached. Theoretical saturation can be defined as "the phase of qualitative data analysis in which the researcher has continued sampling and analyzing data until no new data appear and all concepts of the theory are well-developed and their linkages to other concepts are clearly described" [26]. In Section 4 we start our analysis by considering two main issues, namely techno-economic analysis principles (Section 4.1) and role of energy modelling and analytics (Section 4.2).

4 Rethinking energy services and technologies in buildings

The achievement of stringent energy efficiency goals is one of the crucial elements in energy transition strategies in general, and particularly for the built environment, where the energy savings potential is large and exploited only partially at present. One of the key issues encountered when proposing energy efficiency measures is ensuring their feasibility from a techno-economic perspective, using an appropriate business model.

Energy Performance Contracting (EPC) models [27] are a relevant part of business models routed on energy efficiency, and the role of relevant actors and stakeholders has to be understood in order to engage them successfully. In this sense, barriers such lack of interest, awareness, knowledge and human and financial capacity [28] have to be addressed. Further, it is necessary to consider, from a technical stand-point, the relation between energy performance simulation in design phase (project domain) and measurement and verification practices (M&V) in the operation phase (service domain) [29], following the subdivision of domains reported initially for the construction sector [3]. This can be achieved, for example, by creating integrated data analysis workflows, from design to operation (i.e. linking design and operation phase performance analysis [24]). These workflows can be performed in a semi-automated or automated way using methods that represent an evolution of the state of the art of Measurement and Verification (M&V) protocols developed by ASHRAE [30], Efficiency Value Organization (EVO) [31], Federal Energy Management Program (FEMP) [32], frequently indicated with the term M&V 2.0 [33]. The increasing availability of data generated by smart meters, smart devices, sensors and building management systems can help monitoring, verifying and tracking building energy performance improvements in a transparent way. Large scale data acquisition can potentially take place inexpensively today, considering the state-of-the-art of metering technologies (i.e. smart meters) [34], even though applications should be conceived according to the principle of preserving privacy. Additionally, the use of transparent and standardized methods can help transforming data into useful knowledge for the evolution of products and services, thereby putting continuous learning and improvement cycles in place. From a methodological perspective, Deming cycle or PDCA (Plan-Do-Check-Act) is used as a general tool for the control and continuous improvement of products and processes. More specifically, PDCA is used in energy management systems, as part of current standardization [35], and the improvements achieved by efficiency measures can be compared by means of analytics (i.e. information resulting from the systematic analysis of data) that can be displayed numerically and graphically [36]. The systematic use of energy analytics can become one of the crucial elements for the creation of next generation energy services and technologies in buildings. Hereafter, in Section 4.1, we discuss the role of a techno-economic analysis framework to ensure the feasibility of energy efficiency measures, while in Section 4.2 we illustrate the techniques for energy analytics that can be used to analyse the impact of energy efficiency measures.

4.1 Techno-economic analysis framework

In the last decades, there has been a steady evolution of paradigms for energy efficiency and renewable energy integration in buildings. Concepts such as Net Zero Energy Building (NZEB) [37], Zero Energy Building (ZEB) of Nearly Zero Energy Building (nZEB) [38], Passive House [39], Plus or Positive Energy Building [40] are used by practictioners in new buildings' design and renovation processes. Deep renovations [41], in particular, are radical and therefore expensive, and we are assisting today at lower retrofit rates (i.e. 0.4-1.2% depending on the country) compared to what would be necessary to achieve long-term decarbonisation targets at the EU level [42]. In order to evaluate appropriately the benefits of deep renovations of buildings, a whole life cycle perspective on performance and costs has to be adopted (buildings are long-term assets), because of the significant investments needed and the increase of market value, which can be determined by the improvement of energy rating. Indeed, recent studies highlighted a changing landscape in property valuation [43] determined by energy rating. For this reason, the real estate market impact of energy rating [44] has to be considered as well in the design process, because the willingness to pay for more efficient buildings [45] can open up the space for business opportunities. More in general, deep renovations can contribute to the overall improvement of building characteristics, including Indoor Environmental Quality (IEQ). In fact, the definition of comfort requirement for low energy buildings [46] and their standardization in relation to energy performance assessment [47] is crucial to evaluate the trade-offs between energy performance and comfort conditions [48] (i.e. to find an appropriate balance between comfort and health requirements with respect to energy savings).

In recent years, there has been a development of research around the concept of cost-optimal analysis [49] for effective and transparent techno-economic performance benchmarking of building solutions. The general principles of cost-optimal analysis are described, for example, in the EU Commission Delegated Regulation No 244/2012 [50] and have relevant policy implications. First of all, cost-optimal analysis is based on the concept of Pareto frontier analysis (i.e. the identification of optimal solution with respect to multiple objectives, in this case primary energy and overall cost). The use of Pareto frontier analysis enables the visual identification of the gap among the normative performance limits (for code compliance), the cost-optimal investment levels, the NZEB level, and the maximum performance technically achievable [49]. In this way, three points can be determined that constitute the boundaries of evaluation [51], namely minimum requirements for code compliance, maximum performance achievable and cost-optimal level. The latter represents the set of technological solutions that can achieve a better performance in terms of primary energy and overall project cost compared to minimum requirements. Indeed, the possibility to classify technological solutions with respect to the energy performance thresholds (e.g. nZEB, low energy, new building, major renovation, etc.) [52] and to cluster them into groups is a great advantage when comparing multiple design options [53] at once. Additionally, cost-optimal levels can be identified graphical in a "relative" way by subtracting the baseline cost (i.e. baseline cost become the origin of the y axis) and working on cost differences [54]. From the point of view of technical standardization and harmonization (considered among the constraints in Section 3) cost-optimal analysis method uses a cost accounting scheme that can be found in standard EN 15459-1:2017 [55] and that can framed within the more general Life Cycle Cost (LCC) approach of ISO 15686-5:2017 [56], which can be summarized in the following table, considering the basic subdivision between investment, replacement and running costs in the cash-flow analysis during project duration.

Table 2: Cost accounting in Life Cycle Cost (LCC) analysis for buildings

Type of cost	Process	Cost-accounting (cash-flow analysis)
Investment cost	Design	Initial cost
	Construction	Initial cost
	Refurbishment	Initial cost
	Site management	Initial cost
Periodic Costs	Replacement cost of technologies	Periodic replacement cost
Running Costs	Energy services	Annual cost
	Maintenance	Annual cost
End of Life Costs	Dismantling and disposal, recycling or reuse	End of life cost

In the previous table non-construction cost (e.g. cost of land, fees and enabling costs, externalities) were not indicated as the may not be relevant in the analytical process; however, they are considered in Whole Life Cycle Costs (WLCC) analysis. Given the focus on efficiency, energy savings and cost savings during building operation are the fundamental motivation for higher efficiency (and generally more costly) design solutions in buildings; this is particularly relevant in deep renovations. However, operation and maintenance costs are much more uncertain than initial investment costs, which can be verified by means of data-driven methods [57], considering lumped building characteristics [58]. In fact, empirical studies on building energy "performance gap" have underlined the problem of energy modelling literacy [7] and the need for awareness and training for the use of complex simulation tools [59]. Effects such as "rebound" (i.e. building consumes more than expected, for example in a high efficiency building) [60] or "pre-bound" [61] (i.e. building consumes less than expected, for example in low efficiency building) are frequently encountered in practice and evaluation methodologies have to account for these potential discrepancies [62] and be "calibrated" accordingly. These discrepancies can clearly compromise business opportunities and performance tracking appears crucial to ensure the effectiveness of energy efficiency measures and related cost savings, which justify the creation of a business models built on top of them. Large scale investigations are necessary to document the actual energy, cost and emission savings of energy efficiency measures together with the potential co-benefits and, for this reason, scalability of techniques for energy analytics is one the topics considered in Section 4.2. Hereafter, in Section 4.1.1, we illustrate the state of the art of Energy Performance Contracting (EPC) models, to identify their key components, while in Section 4.1.2 we highlight potential innovations in business models for energy services.

4.1.1 State of the art of Energy Performance Contracting (EPC)

In this paragraph we will illustrate the main types of Energy Performance Contracting models which are different types of agreements between energy customers and Energy Services Companies (ESCOs), or energy services providers more in general. The basic principles of an EPC are shown in Figure 1. In brief, the volume of guaranteed operational cost savings, determined by operational energy savings, has to be higher than the volume of investments (initial investment) in energy efficiency measures, which has to be repaid before the end of contract. As such, the cost components considered in EPC business models are a subset of the ones indicated in Table 2 for LCC analysis and cost-optimal analysis process. Further, as already specified, tracking energy and cost savings during the whole project duration is crucial to ensure the feasibility and robustness of business models.

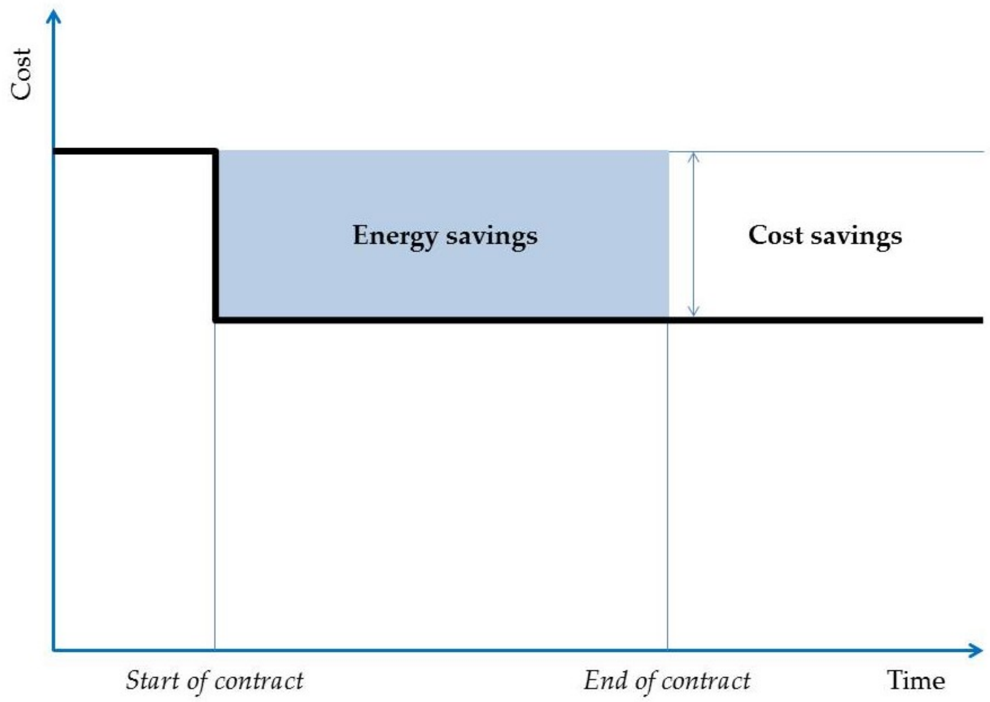

Figure 1: Energy Performance Contracting – Operational energy and cost savings

There are different Energy Performance Contracting models at the state-of-the-art, whose main characteristics are synthesized in Table 4.

Table 3: Fundamental types of EPC with their typical field of applications and characteristics

Type of contract	Typical field of application	Responsibilities	Distribution of savings	Risks
Guaranteed savings (GS)	Built environment/Industry	Design and installation of systems, guarantee of a certain level of energy savings.	Energy savings guaranteed by the ESCO to the client should be sufficient to cover debt service payments.	ESCO assumes performance risk, client assumes credit risk. ESCO can work as a facilitator to access credit.
Shared savings (SS)	Built environment/Industry	ESCO is responsible for design, financing and implementation of the project.	The cost savings are split with respect to a fixed percentage for a fixed period of time, defined by the contract.	ESCO assumes both performance and credit risk ("zero risk" model for client).
Chauffage	Built environment/Industry	ESCO is responsible for the operation and maintenance of the system (complete outsourcing of energy services).	Client is guaranteed an immediate saving relative to its energy bill, expressed in percentage for a period of time defined by the contract.	ESCO assumes both performance and credit risk.
Build-Own-Operate-Transfer (BOOT)	Industry/Power generation plants	ESCO assumes the responsibility of design, installation, financing, operation and maintenance of an equipment owned by the ESCO for a defined period of time and then transferred to the client.	ESCO initially, then client after a period of time defined by the contract.	ESCO initially, then client after the period defined by the contract.
Lease	Industry	In capital lease, the client owns the equipment. In operating lease, the ESCO owns the equipment and the client pays a rent.	Client/ESCO depending on capital or operating lease choice respectively.	Client in the case of capital lease, ESCO in the case of operating lease.

In Guaranteed Savings (GS) model the ESCO assumes the responsibility of design and installation and guarantees a certain level of energy savings. For this reason, the energy customer (client) doesn't assume any performance risk. In turn, ESCO doesn't assume the credit risk, so the client has to be capable of obtaining financing for the project; however the ESCO can work as a facilitator. Energy savings guaranteed by the ESCO should be sufficient to cover debt service payments. In Shared Savings (SS) model the ESCO signs a financing and performance contract with the energy customer (client) and is responsible for design, financing and implementation of the project. The ESCO verifies the energy savings during the contract length. The cost savings (determined by energy savings) are split with respect to a fixed percentage for a fixed period of time. The percentage and period depend on the project characteristics (length of contract, risks, etc.). This model is almost "zero risk" for the client, because the ESCO assumes both the performance and credit risk. In Chauffage model the ESCO takes up the initiative to provide energy performance improvements and the energy customer is guaranteed an immediate saving relative to its energy bill, expressed in percentage. This model represents a form of complete outsourcing of energy services, in which the ESCO is responsible for the operation and maintenance of the energy system. In Build-Own-Operate-Transfer (BOOT) model the ESCO assumes the responsibility of design, installation, financing, operation and maintenance of an equipment that is owned by the ESCO for a defined period of time and then transferred to the client. BOOT are generally long-term contracts in which clients are charged for the service delivered. The service charge includes capital and operating cost recovery and project profit. Finally, in lease model payments tend to be lower than loan payments. This model is commonly used for industrial equipment and the incomes from cost savings are used to cover the lease payment. There are two variations, capital lease and operating lease. In a capital lease, the client owns and depreciates the equipment. In an operating lease, the ESCO owns the equipment and the client pays a rent. In the last case the risk of owning the equipment is transferred from the client to the ESCO.

The most common EPC models used in built environment applications are Guaranteed Savings (GS), Shared Savings (SS), and the Chauffage model. For this three models a graphical representation is proposed respectively in Figures 2, 3 and 4, which indicate the relation between actors (i.e. client, ESCO, bank) and energy (and cost) savings. In this way, the basic constitutive elements of business models focused on energy efficiency are represented visually, linking them ideally to the components in Figure 1 (and consequently to the basic accounting scheme of LCC based cost-optimal analysis in Table 2) and highlighting, in particular, the relation between ESCO, client and bank with respect to the distribution of savings and the payments and financing mechanism. It is worth noting that an important difference between GS and SS models is that in the first case the performance guaranteed is the level of energy saved, while in the second it is the cost of energy saved. While these models differentiate in the way they share energy and cost savings, they keep the fundamental basic mechanism described in Figure 1. Indeed, these two fundamental dimensions (energy and cost savings) are also the ones accounted in cost-optimal analysis [49], both for new buildings and refurbished buildings [63].

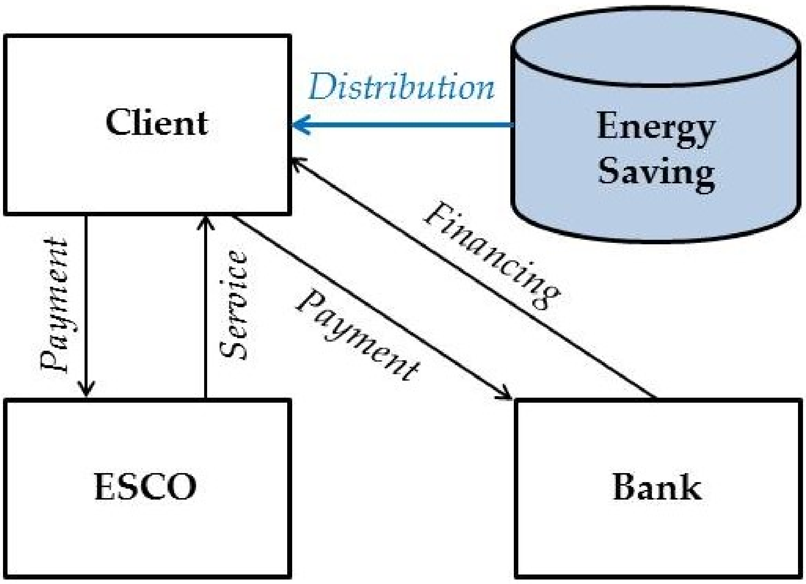

Figure 2: Guaranteed Savings (GS) model for EPC

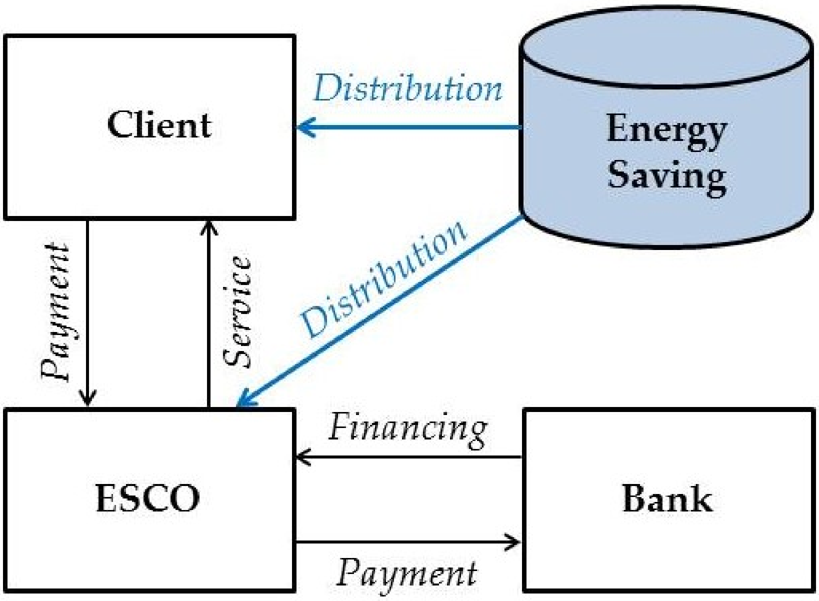

Figure 3: Shared Savings (SS) model for EPC

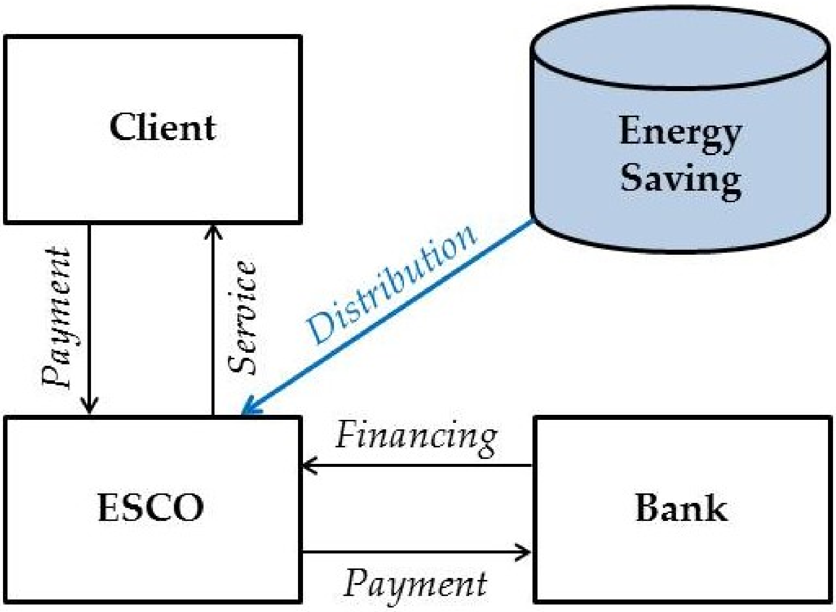

Figure 4: Chauffage model for EPC

4.1.2 Innovative business models for energy services

When business development perspective comes in, the goods to be traded, their price dynamics and the market are the elements to analyse [64]. Data flow in the energy networks is one of these goods already available and owned by the Distribution System Operator (DSO) [65]. Instantaneous electric and volumetric gas flow rate meter readings [66] are not generally used to provide insights to single customers. In some cases, for example above a specific threshold value of the client's power demand, more data are available. For instance, in the electricity market in Italy, customer over 20 kW of power demand can obtain 15-minutes resolution demand and production data as well, if on-site generation (e.g. a grid-connected PV plant) is present. Therefore, the lower the electric power threshold for the customer, the lower the data resolution available. Indeed, looking at residential end-users in Italy whose electricity meter allows from 3 to 6 kW of power, consumption data are given on a monthly base, split into tariff intervals when available. Considering this level of data granularity, recommendations to the clients to actively play with the market are limited to moving their time of use and the requested power to the cheapest tariff interval where loads can be concentrated [67]. Going back to larger consumers, higher data resolution means higher definition of time of use data and a larger set of variables to be considered for the definition of energy and cost saving strategies. From just moving the load, there is the chance to move the energy production time to the one when grid supply is more expensive [68] or even to use storage [69] to reduce or increase demand in the grid in peak and off-peak hours, respectively. Market dynamics practically affect production and distribution, regulation affects energy prices to the clients and clients can act based on the latter input [70]. But, when several customers constitute a group, how their aggregated power demand can be effectively managed becomes an open question and a diffuse demand response approach may be the answer [71]. The size of the group can put it in a position similar the one of large user by means of other subjects such as the aggregator [72] or the Business Responsible Party (BRP) [73], if required. When customers can have access to the balancing market or even ancillary services, other data flows are needed to make informed choices [74] and this is the reason why real time data are gaining more and more consideration [75]. Smart electricity meters and building automation composed by smart plugs, smart appliances and IoT devices gives a wider perspective on the information available for playing within the conventional electricity market [76] and for participating to other markets, allowing actions on individual loads if benefits can be achieved [77]. Moreover, time of information can match time of use enabling further choices [78]. At the same time, distributors have to face congestion, frequency stability or even black-outs as consequence of new power on the Grid from Distributed Generation [79]. Therefore, a room for flexibility and secondary services is important [80]. As a matter fo fact, a number of prosumers can interact each other in terms of energy and data flows [81] taking a step forward towards sharing economy models [82]. Trading based on peer to peer platforms [83] can be adopted as a solution where, rather than exchanging money or energy, goods regulated by law and identified for taxation, the value exchange involves virtual coin and/or virtual power, harnessing the potential of blockchain technology [84] to create energy communities [85]. Imposed payments such as the ones for distribution fees can be progressively eliminated and this explains the bottlenecks [86] for the transition to advanced solution combining IoT, blockchain, new energy market models and automation [87]. On the other hand, increasing the smartness of customers' equipment can contemporary lead to a more efficient and cost saving management from the point of view of the DSO and a lower bill for the customers as an incentive to leave the control of part of their energy use [88].

4.2 The role of energy analytics and modelling

As introduced before, stringent energy efficiency goals are crucial in energy transitions and in the related potential innovative businesses. Two fundamental factors determine energy savings, the increase of performance (expressed as the rate of energy use) and the reduction of operation time (expressed as hours of operation of a certain equipment or system), as shown in Figure 5. In this Figure we depict the results of the application of an energy efficiency measure, for example in a building retrofit. The area of the large box represents the total energy used in the baseline case (before retrofit). Reduction in the rate of energy use (dependent on an increase of performance after retrofit, e.g. increased efficiency of the technology introduced) or reduction in operation time (dependent on a decrease of operating hours, e.g. by means of an efficient management strategy) lead to reduced total energy use, which is represented by the smaller box. The difference between the two boxes (i.e. the shaded area) represents the energy savings. These savings are the ones that enable the fundamental mechanism at the basis of Energy Performance Contracting (EPC) represented in Figure 1 (i.e. energy and cost savings).

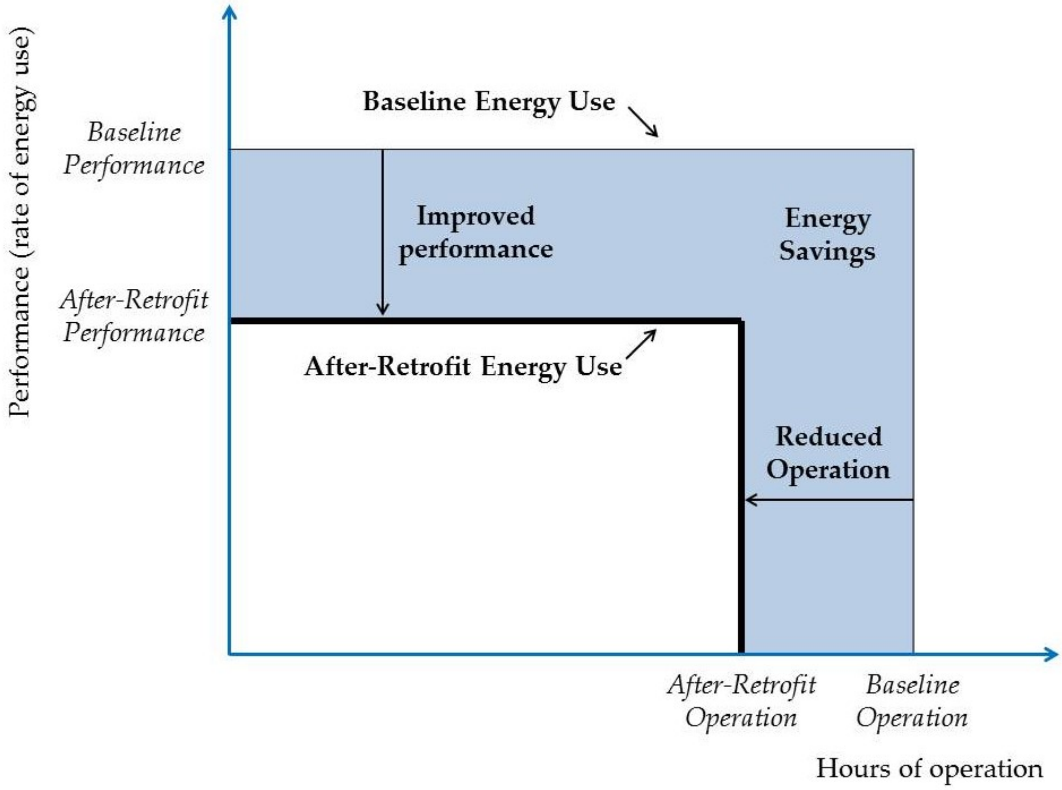

Figure 5: Operational energy savings dependency on performance (rate of energy use) and operation time

This example represent clearly a simplification of a process that is actually taking place dynamically and is influenced by multiple factors [89]; nonetheless, it can be used as a way to illustrate the fundamental principles and to justify the need for energy performance data "normalization" (e.g. with respect to influencing factors such as weather or user behaviour) when addressing energy savings. In fact, from an analytical perspective, it is important to increase the transparency of the methods used for quantifying and exposing energy savings, adopting coherent statistical rules. Today, integrated data analysis workflows for Measurement and Verification (M&V) enable the semi-automated and automated comparison of the performance of multiple statistical/machine learning (data-driven) models [33]. Moving forward in this direction, we can think about integrating the data analysis workflows, from building design to operation phase analysis [24] in a simple, transparent and scalable way [90]. For example, it is possible to analyse building performance (from a statistical perspective) at multiple scales for optimization purpose [91] and to use calibration techniques as a mean to connect design and operation phase analysis [92], acknowledging the inherent uncertainties of the evaluation method in each stage of the building life cycle [93].

Large scale applications of these principles can comprise models suitable for the analysis of building stock decarbonisation [94]**.** Additionally, besides energy, emissions and cost savings, smart energy services and technologies can provide multiple additional benefits such an adequate level of Indoor Environmental Quality (IEQ) [46] and energy flexibility (in the interaction with infrastructures) on the demand side [95], among others. Clearly, an appropriate "compromise" between IEQ levels and energy consumption [48] should be reached to ensure adequate quality of services while enabling savings. Further, appropriate control strategies are necessary for unlocking building flexibility potential, as shown in recent research [96]. For this reason, additional performance indicators will have to be included in M&V to track the performance of innovative energy technologies, interacting with the electric grid dynamically, and this will be an important research area to be developed in the future. Following these arguments, in the next two sections we illustrate, respectively, modelling approaches that can be used at the state of the art for energy modelling and analytics (Section 4.2.1) and how to extend their capabilities (Section 4.2.2) while satisfying the constraints described in methods (Section 3).

4.2.1 State of the art of energy modelling and analytics

We can start by analysing harmonized methods that can help filling the knowledge gap by means of evidence of the actual impact of efficient technologies, e.g. building fabric [97] or innovative controls [98] among others, and that are based on robust and empirically grounded techniques to benchmark energy efficiency measures with a uniform approach [99], which can be extended up to demand response analysis [100] (i.e. addressing dynamic energy demand profiles). The term "harmonized" refers to methodologies in which redundancies and overlapping features produced by different research groups are removed; harmonized methods can help documenting performance transparently and detecting the impact of influencing factors. Of course, appropriate spatial and temporal resolution of data is necessary to track building performance at multiple scales, and energy metering data constitute the basic information layer. Major research initiatives in this direction have been taking place in recent years, such as the Uniform Methods Project (UMP) [99] and other subsequent projects such as Caltrack [101], whose goal was harmonising the methods for quantifying 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.). Harmonised methods are not merely applicable to the built environment, but are also fundamental for research and policy, in general, because they can ensure robust evidence regarding the impact of efficiency measures, by means of reliable statistics. For this reason, Measurement and Verification (M&V) protocols developed by (EVO) [31] and (FEMP) [32] have been used recently also as the basis for projects aimed at de-risking investment in energy efficiency, such as the Investor Confidence Project (ICP) [102].
From a technical perspective, harmonized methods are based on regression and time series analysis and have been developed initially for M&V and Monitoring and Targeting (M&T) purposes, using calibration principles from statistical methods. Therefore, they represent empirically grounded and validated approaches that can be used effectively to provide and track evidence of energy efficiency savings (and also related carbon and cost savings). Additionally, the methods reported in the projects previously mentioned represent an extension of techniques that can be found already in technical standards such as ASHRAE 14:2014 [30], ISO 50006:2014 [36], ISO 16346:2013 [103] and technical guidelines and protocols previously mentioned like EVO [31] and FEMP [32], where specific thresholds (expressed as statistical KPIs) are given for the acceptability of models as calibrated [104],

basically representing their "goodness of fit". Finally, open software for M&V 2.0 (term used to indicate machine learning implementations of M&V methods) is available from RMV2.0 [105], Caltrack [101], recent research articles [106], as well as from other sources. Further software developments in this area, ideally, can be pursed following open science principles (i.e. transparency and reproducibility of results, among others). In general, these methods are based on energy interval data (dependent variable) and on weather data (independent variables), along with other independent variables (e.g. dummy variables to model different occupancy and operational regimes) that can be extracted from contextual information. Instead of using energy data directly, it is possible to transform them to derive the average power over the amount of operating hours in the interval considered, this is called energy signature method [103]. The most important independent variable for weather normalization of energy consumption is outdoor air temperature, which can be used for screening analysis of energy performance [107] and for the detection of anomalies in consumption [108]. These methods are affine to variable-base degree days methods, where the base temperature (for degree-days calculations) can be related to building characteristics [109] or determined for specific areas and groups of buildings [110]. A comprehensive review on temperature response methods can be found in Fazeli et al. [111]. Conceptual simplicity is one of their advantages, compared to other meta-modelling techniques [112] which can be used for calibration [113], and can even automate the process of model selection [106] by means of specific algorithmic implementations [114]. From an analytical perspective, it is important to be able to link both design and operation phase analysis using a robust (with respect to uncertainties) approach [93], based on incremental calibration [92] and periodic recalibration, in order to provide a continuity in the use of energy performance analysis techniques across different life cycle phases [24]. In this way, it becomes possible to generate reliable boundaries for performance measured or estimated [90] and use them against benchmarks, enabling a continuous improvement process (i.e. PDCA, reported before). Far from being simply tools for weather normalization (i.e. to eliminate outdoor air temperature dependence), harmonized methods can help addressing also the dynamic dimension of loads (e.g. demand response) [100], ideally clustering operational conditions for typical daily profiles patterns [115] and recurrent operating schedules (e.g. depending on the type of end-use) [116], with an approach substantially similar to the one used for demand side management in small and medium sized industries [117].

Additionally, the prospect of evaluating with harmonized methods thermal, electrical and fuel requirements can open new possibilities for "soft-linking" of energy models in multi-commodity systems applications [118] from planning and design [119] to operational optimization [120], with the potential of large scale optimization using, for example, Proximal Message Passing technique [121]. In this sense, harmonized methods can supplement (in terms of general principles) open science oriented approaches in energy research [122] because of their transparency. For example, they can help tackling relevant issues such as projections about energy consumption evolution due to climate change [123], by means of "morphed" weather data file [124] in multiple scenarios [125], and definition of load profiles (that can also evolve in time due to efficiency measures and behavioural change, as well as climate change) for decentralized energy systems in buildings [126] and communities such as villages [127] and neighbourhoods [128], where design solutions in planning phase and optimal dispatch strategies (in operation) potentially can be studied in an integrated way [129].

In brief, harmonized methods can be used to address in a robust and transparent way two fundamental dimensions in energy modelling research: quantifying the impact of energy efficiency measures and reconstructing dynamic behaviour (by means time series modelling), for example load profiles. Hereafter, in Table 3, we present a comparison of the fundamental features of regression-based modelling approaches that can fulfill the constraints presented in Section 3. First of all, the literature selected and analysed represent in large part empirically grounded studies where authors used operation phase data. The analysis, in all cases, is conducted using regression-based (interpretable) approaches that are substantially compatible with the principles outlined before in this section, regarding harmonisation and standardization. In terms of temporal scalability, the papers are classified with respect to monthly, daily and hourly data. In some cases sub-hourly data are used as well but we classify them as hourly data because this is the maximum resolution contemplated by thresholds for model calibration proposed in standards and protocols (at the state of the art) [104] and this resolution is sufficient to capture the essence of building dynamic energy behaviour. In terms of spatial scalability, we consider building sub-systems (building fabric and technical systems), whole building, building stock, and community and city scale. For the latter, design corresponds substantially to planning; operation phase data are used as a basis to create reliable projections for the future. Further, whole building energy balance is used in most of the cases, while in some cases (e.g. for building fabric performance assessment) the zone or room level energy balance is considered. Finally, with the term approximate physical interpretation we indicate the possibility to use regression coefficients to estimate physical quantities, for example the Heat Loss Coefficient (HLC) corresponding to the slope of temperature based regression models and balance-point corresponding to the (average) external temperature condition in which energy demand equals to zero. Overall, Table 4 indicates how harmonized/standardized regression-based approaches can span multiple temporal and spatial scales of analysis and how they can, potentially, integrate design and operation phase performance analysis within the same analytical workflow (i.e. satisfying re-configurability constraint reported in Section 3). In synthesis, 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) [29], where dynamic operational conditions are clustered [116] and multiple regression models are combined together [137] to investigate performance, integrating data at multiple spatial and temporal resolutions, while retaining an approximated physical interpretation which can enhance the feedback process. 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-system [159], to networks in multi-energy systems [160]. In the next section we will look at possible ways to extend the inherent capabilities of these modelling approaches by means of physical-statistical formulations, which can provide additional insights in a continuous improvement perspective (i.e. PDCA).

Table 4: Regression-based approaches for energy analytics

References	Temporal scale			Spatial scale					Life cycle phase		Physical interpretation
	Monthly	Daily	Hourly	Building fabric	Technical systems	Whole building	Building stock	Community and city scale	Design	Operation	
Lammers et al. 2011 [130]	✓					✓				✓	
Hallinan et al, 2011 [131]	✓					✓	✓	✓		✓	
Hallinan et al, 2011, [132]	✓			✓	✓	✓	✓	✓		✓	✓
Danov et al., 2011 [133]		✓		✓		✓				✓	✓
Masuda and Claridge, 2012 [134]		✓		✓		✓				✓	✓
Bynum et al., 2012 [135]		✓	✓		✓	✓				✓	✓
Masuda and Claridge, 2014 [107]		✓	✓		✓	✓	✓			✓	✓
Paulus, 2017 [106]	✓	✓	✓			✓				✓	
Paulus et al., 2015 [114]		✓	✓		✓	✓				✓	
Lin and Claridge, 2015 [108]		✓			✓	✓				✓	✓
Hitchin and Knight, 2016 [136]		✓			✓	✓				✓	✓
Jalori and Reddy, 2015 [137]	✓	✓	✓			✓				✓	
Abushakra and Paulus, 2016 [138]			✓			✓				✓	
Bauwens and Roels, 2014 [139]		✓		✓						✓	✓
Erkoreka et al., 2016 [140]		✓	✓	✓						✓	✓
Giraldo-Soto et al., 2018 [141]		✓	✓	✓						✓	✓
Uriarte et al., 2019 [142]		✓	✓	✓						✓	✓
Busato et al. 2012 [143]	✓				✓	✓			✓	✓	✓
Busato et al., 2013 [144]	✓		✓		✓	✓			✓	✓	✓
Krese et al., 2018 [145]			✓			✓				✓	✓
Sjögren et al., 2009 [146]	✓	✓		✓	✓	✓				✓	✓
Vesterberg et al., 2014 [147]	✓	✓		✓	✓	✓				✓	✓
Meng and Mourshed, 2017 [109]		✓	✓			✓	✓			✓	✓
Meng et al., 2020 [148]		✓	✓			✓	✓			✓	
Oh et al., 2020 [34]			✓			✓	✓			✓	
Westermann et al., 2020 [149]			✓		✓	✓	✓			✓	
Pasichnyi et al., 2019 [150]			✓		✓	✓		✓	✓	✓	✓
Qomi et al., 2016 [151]	✓		✓	✓		✓		✓	✓	✓	✓
Afshari et al., 2017 [152]			✓			✓		✓	✓	✓	
Afshari et al., 2017 [153]			✓	✓		✓		✓	✓	✓	✓
Allard et al., 2018 [93]	✓	✓				✓			✓	✓	✓
Tronchin et al., 2018 [92]	✓		✓	✓	✓	✓			✓	✓	
Manfren and Nastasi, 2020 [90]	✓		✓	✓	✓	✓			✓	✓	
Catalina et al., 2008 [154]	✓		✓	✓		✓			✓		✓
Hygh et al., 2012, [155]			✓	✓		✓			✓		
Asadi et al., 2014 [156]			✓	✓	✓	✓			✓		
Al Gharably et al., 2016 [157]			✓	✓		✓			✓		
Ipbüker et al., 2016 [158]			✓	✓		✓			✓		

4.2.2 Future research directions for energy modelling

In this section some possibile extensions of the methods and models presented in the previous section are discussed. First, scalability (temporal and spatial) and interpretability constitute, in our opinion, two essential constraints that are specifically indicated as part of the review methods, described in Section 3. We have to consider the fact that interpretable (e.g. regression-based) data-driven models can be formulated using a physical-statistical interpretation of model coefficients (i.e. moving from a “black-box” to a “grey-box” formulation, starting from the simplification of zone level energy balance [139]) suitable for multi-scale analysis [91] and, more specifically, as an analytical tool that can support the decarbonisation process [94] where metered whole building energy consumption and outdoor air temperature constitute the basic information [161] and can be complemented by measurements of thermo-physical properties [162] and other contextual information. Despite the variety of possible model formulations, we believe that data-driven approaches should be using building energy modelling definitions and quantities coherent with the ones proposed in current technical standardization [163], to enhance comparability of results and consistency with policy objectives, for which standardization plays a fundamental role. In this sense, we can find methods for the identification of thermophysical properties of building construction components and thermal zones such as QUB [164], which enables fast in situ measurements [165], and ISABELE [166]. In both cases, the definitions used in models are in line with current technical standardization; physical parameters are expressed with lumped quantities (thus minimising the amount of parameters needed), and model formulation represents substantially a reduction of a detailed physical "white-box" model. “White-box” models are detailed models based on physical laws used mostly for simulations in the design phase (and validated in compliance with energy simulation test standards such as ISO 52016-1:2017 [167] and ASHRAE 140:2017 [168]). We can find a point of contact between “white-box” detailed modelling and “grey-box”lumped parameter modelling, in multi-level building energy model calibration where “macro-parameters” (aggregated, lumped quantities) are used to validate more detailed models [169]. In fact, a potential advantage of “grey-box” models is that they can be formulated (and verified) from basic energy analysis principles derived from thermodynamics [170] and represented schematically as thermal networks [171], with definitions compatible with technical standardization such as ISO 13790:2008 [172] and ISO 52016-1:2017 [173]. Further, “grey-box” models can then be converted to “black-box” models (i.e. statistical and machine learning models) for specific applications [174]. “Black box” models are computationally efficient but they need to be trained on data before being used. Therefore, “grey-box” models can be considered as a intermediate step between “white-box” and “black-box” models and we can find in recent years several examples of application, from experimental test-facilities of building technologies [175], to integration within Building Information Modelling (BIM) workflows [176] and also to integrated room automation [177]. Additionally, regression-based (described in Section 4.2.1) and “grey-box” models’ capabilities can be extended in a Bayesian framework. Bayesian analysis is suitable, for example, to “reconstruct” building stock [178] “micro-level” models from “macro-level” data [179] and use them for prediction with uncertainty quantitification [180]. Along the same line, Bayesian analysis can used as well to test the robustness of “grey-box” models’ estimates with respect to variable operational conditions [181] using Monte Carlo simulation methods [182], to reproduce uncertain operational conditions realistically. What appears to be important for future research in this area is increasing the transparency of the modelling process by means of harmonized methodologies (using standardized rules and interpretable models, as discussed before, to verify and track performance efficiently) and enhancing their level of automation without increasing unnecessarily the complexity of implementation. Indeed, with respect to automation, modelling transparency is essential for Model Predictive Control (MPC) formulations [183], which can enhance energy efficiency further compared to the state of the art [184]. Building Automation and Control Systems (BACS) [185] and energy and environmental monitoring systems [186] are necessary to control and collect data on performance (starting from energy metering, of course, which constitutes the basic level of information), considering the inherent uncertainty of measurements [187]. Finally, surrogate physical-statistical models (i.e. "grey-box" models), in general, can be implemented in cyber-physical systems for IoT applications [188] and work as systems of models [189]. Essentially they can act as "digital twins," that is to say digital reproductions of the dynamic behaviour of their physical counterparts, which can operate in a coordinated way, following common underlying modelling principles.

5 Recommendations and further work

In Section 4.2.2 we described how it is possible to create a modelling framework that satisfies the criteria specified in Section 3 and that can support the business models described in Section 4.1. One of the fundamental objectives of a modelling framework is reducing the level of fragmentation and increasing the transparency in the way methods and models are used in practice and, eventually, combined together in an analytical workflow. The research community in the energy field has stressed in recent years the fundamental importance of open energy data and models [190], together with the transparency of modelling techniques [191]. Therefore, we can envisage an evolution towards systems of model [189] designed to address key problems in energy transitions, eventually taking advantage of "soft-linking" approaches, e.g. between energy and power systems models [192], to evaluate the potential of flexibility already at the planning level [193]. Rather than being designed for separate applications, potentially models can be conceived and work like "ecosystems" [189] of interconnected applications, based on open data and modelling standards [23], overcoming the current limitations [190] and, in particular, increasing modelling transparency [191]. Further they can be integrated within innovative business models to determine techno-economically feasible pathways in energy transitions, thereby enabling a radical change to happen in practice. Models, in our opinion, have to share a set of common features (e.g. empirically grounding, harmonization/standardization, scalability, interpretability, re-configurability, described in Section 3) in order to work effectively in "ecosystems" and this the fundamental reason why we introduced these features as constraints in the research process. One of the main advantages of regression-based techniques is their conceptual simplicity and robustness, connected to interpretability. Furthermore, in a decentralised energy systems perspective, the complexity of issues to be addressed for optimal building design and operation increases, as end-users are not simply "consumers" anymore but "prosumers" (producers/consumers) [194] or "prosumagers" (prosumer/aggregators) that can exploit the peer-to-peer trading and storage opportunities [195] to create innovative business models [196]. Additionally, decentralization determines the need to examine in more detail the co-evolution of built environment and energy infrastructures [22] and to investigate potential of "soft-linking" approaches, from energy planning to operation [193]. Advances in data interoperability (technical, informational and organizational) [197] and data availability at multiple levels can represent an additional enabling factor in this direction. Infrastructures and technologies such as the Internet of Things (IoT), characterized by distributed intelligence [198], enabled in turn by effective Machine-to-Machine (M2M) communication [199] and computing [200], are essential for disruptive innovations in the built environment [188], in end-user energy delivery [201], and in energy infrastructures [202], where peer-to-peer automated exchange mechanisms using Blockchain technologies [203] could represent a major breakthrough. In this rapidly evolving landscape, research aimed at radical changes in energy systems and built environment needs to address the issues reported above in order to ensure coherency and consistency of actions towards energy efficiency and carbon reduction goals. Harmonized methods and models to track performance in buildings (at multiple scales) can help extracting insights for continuous improvement, becoming a core element for the evolution of the energy sector. Further dimensions can be include in the modelling process by exploiting contextual information; it this way it becomes possible to create applications tailored for specific needs that are sharing, however, similar underlying principles, as discussed in the previous section.

6 Conclusion

Smart energy services and technologies are key components of energy transition strategies because they can dramatically increase the energy efficiency and renewable energy penetration levels in the built environment. The development of strategies for energy transitions and decarbonisation requires the conceptualization of how radical changes can take place while fulfilling fundamental societal needs. A possible conceptualization of the construction sector comprises three domains: project, product, service. By leveraging the multiple feedback loops generated by data analytics from smart energy services and technologies, all of these domains have the potential to evolve significantly. Furthermore, in order to enable radical shifts, processes and practices in the built environment must co-evolve with those in energy infrastructures, recognizing the fundamental complementarities. For this reason, in this paper we considered techno-economic analysis and energy modelling as key enablers for next-generation energy services and technologies in buildings. After defining the key elements of life cycle costing approaches in building projects in Section 4.1 (using LCC cost-optimal analysis as the reference method), we discussed concepts at the state of the art for Energy Performance Contracting in Section 4.1.1, highlighting critical dimensions such as the relations among the actors involved, the way energy and cost savings are shared, and the payment and financing mechanisms. Then, we presented in Section 4.1.2 possible innovations regarding energy services enabled by data analytics, in particular peer-to-peer energy trading for prosumers, prosumagers and energy communities, which can extend the reach and impact of innovative energy services. After that, we illustrated the state of the art of energy modelling techniques that can fulfill the criteria reported in Section 3, considered as limiting factors for future developments. In Section 4.2.1 we summarized the basic structure of a “unified” framework of analysis, highlighting the temporal and spatial scalability of regression-based approaches, which could enable seamless integration of the data analysis workflows (during different building life-cycle phases) and multiple feedback loops, thanks to their interpretability. This framework can evolve further by means of standardized “grey-box” physical-statistical models that can be implemented in monitoring and automation systems, as indicated in Section 4.2.2. In general, we stressed the importance of linking multiple domains of knowledge in built environment research, using techno-economic analysis and energy modelling as focal elements. Possible further research efforts involve the creation of "ecosystems" of interacting applications, based on open data and modelling standards, which can provide multiple benefits both for prosumers/prosumagers and energy communities, as well as for energy infrastructures. As a conclusion, in this paper we illustrated some of the key concepts that are relevant for the implementation of innovative processes and practices in the building sector today. These concepts are transparently and explicitly linked to consolidated results from previous research and can be used to promote and orient future research initiatives in the broad area of energy transitions and decarbonisation of the built environment. This can help accelerating the process of radical change, required to achieve long-term sustainability goals, by pursuing a continuous improvement logic.

Acknowledgements

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

References

[1] Loorbach D, Frantzeskaki N, Avelino F. Sustainability Transitions Research: Transforming Science and Practice for Societal Change. Annu Rev Environ Resour 2017. https://doi.org/10.1146/annurev-environ-102014-021340.

[2] Köhler J, Geels FW, Kern F, Markard J, Onsongo E, Wieczorek A, et al. An agenda for sustainability transitions research: State of the art and future directions. Environ Innov Soc Transitions 2019;31:1–32. https://doi.org/https://doi.org/10.1016/j.eist.2019.01.004.

[3] Thuesen C, Koch-Ørvad N, Maslesa E. Organising Sustainable Transition: Understanding the Product, Project and Service Domain of the Built Environment. 32nd Annu. ARCOM Conf., 2016.

[4] Within G. a circular economy vision for a competitive Europe. Ellen Macarthur Found 2015:1–98.

[5] Pomponi F, Moncaster A. Circular economy for the built environment: A research framework. J Clean Prod 2017;143:710–8. https://doi.org/https://doi.org/10.1016/j.jclepro.2016.12.055.

[6] De Wolf C, Pomponi F, Moncaster A. Measuring embodied carbon dioxide equivalent of buildings: A review and critique of current industry practice. Energy Build 2017;140:68–80. https://doi.org/https://doi.org/10.1016/j.enbuild.2017.01.075.

[7] Imam S, Coley DA, Walker I. The building performance gap: Are modellers literate? Build Serv Eng Res Technol 2017;38:351–75. https://doi.org/10.1177/0143624416684641.

[8] de Wilde P. "The building performance gap: Are modellers literate?" Build Serv Eng Res Technol 2017;38:757–9. https://doi.org/10.1177/0143624417728431.

[9] Pomponi F, Moncaster A. Scrutinising embodied carbon in buildings: The next performance gap made manifest. Renew Sustain Energy Rev 2018;81:2431–42. https://doi.org/https://doi.org/10.1016/j.rser.2017.06.049.

[10] Pannier M-L, Schalbart P, Peuportier B. Comprehensive assessment of sensitivity analysis methods for the identification of influential factors in building life cycle assessment. J Clean Prod 2018;199:466–80.

https://doi.org/https://doi.org/10.1016/j.jclepro.2018.07.070.
[11] Markard J, Raven R, Truffer B. Sustainability transitions: An emerging field of research and its prospects. Res Policy 2012;41:955–67. https://doi.org/https://doi.org/10.1016/j.respol.2012.02.013.
[12] Markard J, Hoffmann VH. Analysis of complementarities: Framework and examples from the energy transition. Technol Forecast Soc Change 2016;111:63–75. https://doi.org/https://doi.org/10.1016/j.techfore.2016.06.008.
[13] Lindberg MB, Markard J, Andersen AD. Policies, actors and sustainability transition pathways: A study of the EU's energy policy mix. Res Policy 2019;48:103668. https://doi.org/https://doi.org/10.1016/j.respol.2018.09.003.
[14] Gibbs D, O'Neill K. Building a green economy? Sustainability transitions in the UK building sector. Geoforum 2015;59:133–41. https://doi.org/https://doi.org/10.1016/j.geoforum.2014.12.004.
[15] Schot J, Geels FW. Strategic niche management and sustainable innovation journeys: Theory, findings, research agenda, and policy. Technol Anal Strateg Manag 2008. https://doi.org/10.1080/09537320802292651.
[16] Creswell JW, Creswell JD. Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications; 2017.
[17] Birks M, Mills J. Grounded theory: A practical guide. Sage; 2015.
[18] Glaser BG. Doing grounded theory: Issues and discussions. Sociology Press; 1998.
[19] Glaser BG, Holton J. Remodeling grounded theory. Forum Qual. sozialforschung/forum Qual. Soc. Res., vol. 5, 2004.
[20] Corbin J, Strauss A. Basics of qualitative research: Techniques and procedures for developing grounded theory. Sage publications; 2014.
[21] Charmaz K. Constructionism and the grounded theory method. Handb Constr Res 2008;1:397–412.
[22] Tronchin L, Manfren M, Nastasi B. Energy efficiency, demand side management and energy storage technologies – A critical analysis of possible paths of integration in the built environment. Renew Sustain Energy Rev 2018;95:341–53. https://doi.org/https://doi.org/10.1016/j.rser.2018.06.060.
[23] Manfren M, Nastasi B, Groppi D, Astiaso Garcia D. Open data and energy analytics - An analysis of essential information for energy system planning, design and operation. Energy 2020;213. https://doi.org/10.1016/j.energy.2020.118803.
[24] Manfren M, Nastasi B, Tronchin L. Linking Design and Operation Phase Energy Performance Analysis Through Regression-Based Approaches. Front Energy Res 2020;8:288. https://doi.org/10.3389/fenrg.2020.557649.
[25] Manfren M, Sibilla M, Tronchin L. Energy Modelling and Analytics in the Built Environment—A Review of Their Role for Energy Transitions in the Construction Sector. Energies 2021;14. https://doi.org/10.3390/en14030679.
[26] Morse JM, Lewis-Beck M, Bryman AE, Liao TF. The SAGE encyclopedia of social science research methods 2004.
[27] Shang T, Zhang K, Liu P, Chen Z. A review of energy performance contracting business models: Status and recommendation. Sustain Cities Soc 2017;34:203–10. https://doi.org/https://doi.org/10.1016/j.scs.2017.06.018.
[28] Winther T, Gurigard K. Energy performance contracting (EPC): a suitable mechanism for achieving energy savings in housing cooperatives? Results from a Norwegian pilot project. Energy Effic 2017;10:577–96. https://doi.org/10.1007/s12053-016-9477-0.

[29] Ligier S, Robillart M, Schalbart P, Peuportier B. Energy Performance Contracting Methodology Based upon Simulation and Measurement. Build. Simul. 2017, San Francisco, United States: 2017.
[30] ASHRAE. ASHRAE Guideline 14-2014: Measurement of Energy, Demand, and Water Savings; American Society of Heating, Refrigerating and Air-Conditioning Engineers: Atlanta, GA, USA, 2014. 2014.
[31] EVO. IPMVP New Construction Subcommittee. International Performance Measurement & Verification Protocol: Concepts and Option for Determining Energy Savings in New Construction, Volume III; Efficiency Valuation Organization (EVO): Washington, DC, USA, 2003 2003.
[32] FEMP. FEMP. Federal Energy Management Program, M&V Guidelines: Measurement and Verification for Federal Energy Projects Version 3.0, U.S. Department of Energy Federal Energy Management Program 2008.
[33] Gallagher C V, Leahy K, O'Donovan P, Bruton K, O'Sullivan DTJ. Development and application of a machine learning supported methodology for measurement and verification (M&V) 2.0. Energy Build 2018;167:8–22. https://doi.org/https://doi.org/10.1016/j.enbuild.2018.02.023.
[34] Oh S, Haberl JS, Baltazar J-C. Analysis methods for characterizing energy saving opportunities from home automation devices using smart meter data. Energy Build 2020:109955. https://doi.org/https://doi.org/10.1016/j.enbuild.2020.109955.
[35] ISO 50001:2018, Energy management systems - Requirements with guidance for use 2018.
[36] ISO 50006:2014, Energy management systems — Measuring energy performance using energy baselines (EnB) and energy performance indicators (EnPI) — General principles and guidance 2014.
[37] Deng S, Wang RZ, Dai YJ. How to evaluate performance of net zero energy building – A literature research. Energy 2014;71:1–16. https://doi.org/https://doi.org/10.1016/j.energy.2014.05.007.
[38] Berardi U. ZEB and nZEB (definitions, design methodologies, good practices, and case studies). Handb Energy Effic Build A Life Cycle Approach 2018:88.
[39] Wang Y, Kuckelkorn J, Zhao F-Y, Spliethoff H, Lang W. A state of art of review on interactions between energy performance and indoor environment quality in Passive House buildings. Renew Sustain Energy Rev 2017;72:1303–19. https://doi.org/https://doi.org/10.1016/j.rser.2016.10.039.
[40] Magrini A, Lentini G, Cuman S, Bodrato A, Marenco L. From nearly zero energy buildings (NZEB) to positive energy buildings (PEB): The next challenge - The most recent European trends with some notes on the energy analysis of a forerunner PEB example. Dev Built Environ 2020;3:100019. https://doi.org/https://doi.org/10.1016/j.dibe.2020.100019.
[41] D'Oca S, Ferrante A, Ferrer C, Pernetti R, Gralka A, Sebastian R, et al. Technical, Financial, and Social Barriers and Challenges in Deep Building Renovation: Integration of Lessons Learned from the H2020 Cluster Projects. Build 2018;8. https://doi.org/10.3390/buildings8120174.
[42] European Commission. European Commision. (2020). Working programme 2018-2020. Secure, clean and efficient energy. European Commission Decision C(2020)6320 of 17 September 2020 (https://ec.europa.eu/research/participants/data/ref/h2020/wp/2018-2020/main/h2020-wp1820-energy_en. n.d.
[43] Wilkinson S, Sayce S. Energy efficiency and residential values: a changing

European landscape - RICS (Royal Institution of Chartered Surveyors) 2019.
[44] Fabbri K, Tronchin L, Tarabusi V. Real Estate market, energy rating and cost. Reflections about an Italian case study. Procedia Eng 2011;21:303–10. https://doi.org/https://doi.org/10.1016/j.proeng.2011.11.2019.
[45] Brocklehurst F. What will you pay for an“ A”?-a review of the impact of building energy efficiency labelling on building value. ECEEE Summer Study, 2017, p. 1259–69.
[46] Zangheri P, Pagliano L, Armani R. How the comfort requirements can be used to assess and design low energy buildings: testing the EN 15251 comfort evaluation procedure in 4 buildings. eceee 2011 Summer Study" Energy Effic. first Found. a low-carbon Soc., 2011, p. 1569–79.
[47] Fabbri K, Tronchin L. Indoor Environmental Quality in Low Energy Buildings. Energy Procedia 2015;78:2778–83. https://doi.org/https://doi.org/10.1016/j.egypro.2015.11.625.
[48] Manfren M, Nastasi B, Piana E, Tronchin L. On the link between energy performance of building and thermal comfort: An example. AIP Conf Proc 2019;2123:20066. https://doi.org/10.1063/1.5116993.
[49] Ferrara M, Monetti V, Fabrizio E. Cost-Optimal Analysis for Nearly Zero Energy Buildings Design and Optimization: A Critical Review. Energies 2018;11. https://doi.org/10.3390/en11061478.
[50] European Commission. COMMISSION DELEGATED REGULATION (EU) No 244/2012 of 16 January 2012 2012.
[51] Araújo C, Almeida M, Bragança L, Barbosa JA. Cost–benefit analysis method for building solutions. Appl Energy 2016;173:124–33. https://doi.org/https://doi.org/10.1016/j.apenergy.2016.04.005.
[52] Kuusk K, Kalamees T, Pihelo P. Experiences from Design Process of Renovation of Existing Apartment Building to nZEB. CLIMA, 2016.
[53] Mutani G, Cornaglia M, Berto M. Improving energy sustainability for public buildings in Italian mountain communities. Heliyon 2018;4:e00628. https://doi.org/https://doi.org/10.1016/j.heliyon.2018.e00628.
[54] Ascione F, Bianco N, De Stasio C, Mauro GM, Vanoli GP. CASA, cost-optimal analysis by multi-objective optimisation and artificial neural networks: A new framework for the robust assessment of cost-optimal energy retrofit, feasible for any building. Energy Build 2017;146:200–19. https://doi.org/https://doi.org/10.1016/j.enbuild.2017.04.069.
[55] EN 15459-1. Energy performance of buildings - Economic evaluation procedure for energy systems in buildings - Part 1 2017.
[56] ISO 15686-5. Buildings and constructed assets — Service life planning — Part 5: Life-cycle costing 2017.
[57] Kim G-H, An S-H, Kang K-I. Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning. Build Environ 2004;39:1235–42. https://doi.org/https://doi.org/10.1016/j.buildenv.2004.02.013.
[58] Alshamrani OS. Construction cost prediction model for conventional and sustainable college buildings in North America. J Taibah Univ Sci 2017;11:315–23. https://doi.org/https://doi.org/10.1016/j.jtusci.2016.01.004.
[59] de Wilde P. The gap between predicted and measured energy performance of buildings: A framework for investigation. Autom Constr 2014;41:40–9. https://doi.org/http://doi.org/10.1016/j.autcon.2014.02.009.
[60] Herring H, Roy R. Technological innovation, energy efficient design and the

rebound effect. Technovation 2007;27:194–203. https://doi.org/https://doi.org/10.1016/j.technovation.2006.11.004.
[61] Sunikka-Blank M, Galvin R. Introducing the prebound effect: the gap between performance and actual energy consumption. Build Res Inf 2012;40:260–73. https://doi.org/10.1080/09613218.2012.690952.
[62] Rosenow J, Galvin R. Evaluating the evaluations: Evidence from energy efficiency programmes in Germany and the UK. Energy Build 2013;62:450–8. https://doi.org/https://doi.org/10.1016/j.enbuild.2013.03.021.
[63] Tronchin L, Tommasino MC, Fabbri K. On the "cost-optimal levels" of energy performance requirements and its economic evaluation in Italy. Int J Sustain Energy Plan Manag 2014;3:49–62.
[64] Kezunovic M, Pinson P, Obradovic Z, Grijalva S, Hong T, Bessa R. Big data analytics for future electricity grids. Electr Power Syst Res 2020;189:106788. https://doi.org/https://doi.org/10.1016/j.epsr.2020.106788.
[65] Buchmann M. How decentralization drives a change of the institutional framework on the distribution grid level in the electricity sector – The case of local congestion markets. Energy Policy 2020;145:111725. https://doi.org/https://doi.org/10.1016/j.enpol.2020.111725.
[66] Stagnaro C, Benedettini S. Chapter 12 - Smart meters: the gate to behind-the-meter? In: Sioshansi FBT-B and B the M, editor., Academic Press; 2020, p. 251–65. https://doi.org/https://doi.org/10.1016/B978-0-12-819951-0.00012-8.
[67] Ambrosio-Albala P, Middlemiss L, Owen A, Hargreaves T, Emmel N, Gilbertson J, et al. From rational to relational: How energy poor households engage with the British retail energy market. Energy Res Soc Sci 2020;70:101765. https://doi.org/https://doi.org/10.1016/j.erss.2020.101765.
[68] Lund H, Andersen AN. Optimal designs of small CHP plants in a market with fluctuating electricity prices. Energy Convers Manag 2005;46:893–904. https://doi.org/https://doi.org/10.1016/j.enconman.2004.06.007.
[69] Garmabdari R, Moghimi M, Yang F, Lu J. Multi-objective optimisation and planning of grid-connected cogeneration systems in presence of grid power fluctuations and energy storage dynamics. Energy 2020;212:118589. https://doi.org/https://doi.org/10.1016/j.energy.2020.118589.
[70] Ribó-Pérez D, Van der Weijde AH, Álvarez-Bel C. Effects of self-generation in imperfectly competitive electricity markets: The case of Spain. Energy Policy 2019;133:110920. https://doi.org/https://doi.org/10.1016/j.enpol.2019.110920.
[71] Darby SJ. Demand response and smart technology in theory and practice: Customer experiences and system actors. Energy Policy 2020;143:111573. https://doi.org/https://doi.org/10.1016/j.enpol.2020.111573.
[72] Mancini F, Romano S, Basso G Lo, Cimaglia J, Santoli L de. How the Italian Residential Sector Could Contribute to Load Flexibility in Demand Response Activities: A Methodology for Residential Clustering and Developing a Flexibility Strategy. Energies 2020;13:3359.
[73] Yousefi Ramandi M, Bigdeli N, Afshar K. Stochastic economic model predictive control for real-time scheduling of balance responsible parties. Int J Electr Power Energy Syst 2020;118:105800. https://doi.org/https://doi.org/10.1016/j.ijepes.2019.105800.
[74] Hamwi M, Lizarralde I, Legardeur J. Demand response business model canvas: A tool for flexibility creation in the electricity markets. J Clean Prod 2020:124539. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.124539.
[75] Steriotis K, Tsaousoglou G, Efthymiopoulos N, Makris P, Varvarigos E (Manos).

A novel behavioral real time pricing scheme for the active energy consumers' participation in emerging flexibility markets. Sustain Energy, Grids Networks 2018;16:14–27. https://doi.org/https://doi.org/10.1016/j.segan.2018.05.002.
[76] Sharda S, Singh M, Sharma K. Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities. Sustain Cities Soc 2020:102517. https://doi.org/https://doi.org/10.1016/j.scs.2020.102517.
[77] Immonen A, Kiljander J, Aro M. Consumer viewpoint on a new kind of energy market. Electr Power Syst Res 2020;180:106153. https://doi.org/https://doi.org/10.1016/j.epsr.2019.106153.
[78] Gans W, Alberini A, Longo A. Smart meter devices and the effect of feedback on residential electricity consumption: Evidence from a natural experiment in Northern Ireland. Energy Econ 2013;36:729–43. https://doi.org/https://doi.org/10.1016/j.eneco.2012.11.022.
[79] Johansson P, Vendel M, Nuur C. Integrating distributed energy resources in electricity distribution systems: An explorative study of challenges facing DSOs in Sweden. Util Policy 2020;67:101117. https://doi.org/https://doi.org/10.1016/j.jup.2020.101117.
[80] Lezama F, Soares J, Canizes B, Vale Z. Flexibility management model of home appliances to support DSO requests in smart grids. Sustain Cities Soc 2020;55:102048. https://doi.org/https://doi.org/10.1016/j.scs.2020.102048.
[81] Jackson Inderberg TH, Sæle H, Westskog H, Winther T. The dynamics of solar prosuming: Exploring interconnections between actor groups in Norway. Energy Res Soc Sci 2020;70:101816. https://doi.org/https://doi.org/10.1016/j.erss.2020.101816.
[82] Filipović S, Radovanović M, Lior N. What does the sharing economy mean for electric market transitions? A review with sustainability perspectives. Energy Res Soc Sci 2019;58:101258. https://doi.org/https://doi.org/10.1016/j.erss.2019.101258.
[83] Buth MC (Annemarie), Wieczorek AJ (Anna), Verbong GPJ (Geert). The promise of peer-to-peer trading? The potential impact of blockchain on the actor configuration in the Dutch electricity system. Energy Res Soc Sci 2019;53:194–205. https://doi.org/https://doi.org/10.1016/j.erss.2019.02.021.
[84] Han D, Zhang C, Ping J, Yan Z. Smart contract architecture for decentralized energy trading and management based on blockchains. Energy 2020;199:117417. https://doi.org/https://doi.org/10.1016/j.energy.2020.117417.
[85] Gui EM, MacGill I. Typology of future clean energy communities: An exploratory structure, opportunities, and challenges. Energy Res Soc Sci 2018. https://doi.org/10.1016/j.erss.2017.10.019.
[86] Hoarau Q, Perez Y. Network tariff design with prosumers and electromobility: Who wins, who loses? Energy Econ 2019;83:26–39. https://doi.org/https://doi.org/10.1016/j.eneco.2019.05.009.
[87] Di L, Yuan GX, Zeng T, Zhang Q, Zhang X. The Existence of Consensus Equilibria for Data Trading under the Framework of Internet of Things (IoT) with Blockchain Ecosystems. Procedia Comput Sci 2020;174:55–65. https://doi.org/https://doi.org/10.1016/j.procs.2020.06.056.
[88] Kaufmann S, Künzel K, Loock M. Customer value of smart metering: Explorative evidence from a choice-based conjoint study in Switzerland. Energy Policy 2013;53:229–39. https://doi.org/https://doi.org/10.1016/j.enpol.2012.10.072.
[89] Yoshino H, Hong T, Nord N. IEA EBC annex 53: Total energy use in

buildings—Analysis and evaluation methods. Energy Build 2017;152:124–36. https://doi.org/https://doi.org/10.1016/j.enbuild.2017.07.038.
[90] Manfren M, Nastasi B. Parametric Performance Analysis and Energy Model Calibration Workflow Integration—A Scalable Approach for Buildings. Energies 2020;13. https://doi.org/10.3390/en13030621.
[91] Tronchin L, Manfren M, Tagliabue LC. Optimization of building energy performance by means of multi-scale analysis – Lessons learned from case studies. Sustain Cities Soc 2016;27:296–306. https://doi.org/https://doi.org/10.1016/j.scs.2015.11.003.
[92] Tronchin L, Manfren M, James PAB. Linking design and operation performance analysis through model calibration: Parametric assessment on a Passive House building. Energy 2018;165:26–40. https://doi.org/https://doi.org/10.1016/j.energy.2018.09.037.
[93] Allard I, Olofsson T, Nair G. Energy evaluation of residential buildings: Performance gap analysis incorporating uncertainties in the evaluation methods. Build. Simul., vol. 11, 2018, p. 725–37.
[94] Tronchin L, Manfren M, Nastasi B. Energy analytics for supporting built environment decarbonisation. Energy Procedia 2019;157:1486–93. https://doi.org/https://doi.org/10.1016/j.egypro.2018.11.313.
[95] Junker RG, Azar AG, Lopes RA, Lindberg KB, Reynders G, Relan R, et al. Characterizing the energy flexibility of buildings and districts. Appl Energy 2018;225:175–82. https://doi.org/https://doi.org/10.1016/j.apenergy.2018.05.037.
[96] Clauß J, Finck C, Vogler-Finck P, Beagon P. Control strategies for building energy systems to unlock demand side flexibility--A review. IBPSA Build. Simul. 2017, San Fr. 7-9 August 2017, 2017.
[97] Jack R, Loveday D, Allinson D, Lomas K. First evidence for the reliability of building co-heating tests. Build Res Inf 2018;46:383–401. https://doi.org/10.1080/09613218.2017.1299523.
[98] Lomas KJ, Oliveira S, Warren P, Haines VJ, Chatterton T, Beizaee A, et al. Do domestic heating controls save energy? A review of the evidence. Renew Sustain Energy Rev 2018;93:52–75. https://doi.org/https://doi.org/10.1016/j.rser.2018.05.002.
[99] Jayaweera T, Haeri H, Gowans D. The Uniform Methods Project: Methods for Determining Energy Efficiency Savings for Specific Measures. Contract 2013;303:275–3000.
[100] Mathieu JL, Price PN, Kiliccote S, Piette MA. Quantifying changes in building electricity use, with application to demand response. IEEE Trans Smart Grid 2011;2:507–18.
[101] CalTRACK. CalTRACK Methods (http://docs.caltrack.org/en/latest/methods.html), accessed on 21/04/2021.
[102] Investor Confidence Project (https://europe.eeperformance.org/), accessed 21/04/2021.
[103] ISO 16346:2013, Energy performance of buildings — Assessment of overall energy performance 2013.
[104] Fabrizio E, Monetti V. Methodologies and Advancements in the Calibration of Building Energy Models. Energies 2015;8:2548.
[105] RMV2.0 - LBNL M&V2.0 Tool (https://lbnl-eta.github.io/RMV2.0/), accessed on 21/04/2021.
[106] Paulus MT. Algorithm for explicit solution to the three parameter linear change-point regression model. Sci Technol Built Environ 2017;23:1026–35.

[107] Masuda H, Claridge DE. Statistical modeling of the building energy balance variable for screening of metered energy use in large commercial buildings. Energy Build 2014;77:292–303. https://doi.org/https://doi.org/10.1016/j.enbuild.2014.03.070.
[108] Lin G, Claridge DE. A temperature-based approach to detect abnormal building energy consumption. Energy Build 2015;93:110–8. https://doi.org/https://doi.org/10.1016/j.enbuild.2015.02.013.
[109] Meng Q, Mourshed M. Degree-day based non-domestic building energy analytics and modelling should use building and type specific base temperatures. Energy Build 2017;155:260–8. https://doi.org/https://doi.org/10.1016/j.enbuild.2017.09.034.
[110] Kohler M, Blond N, Clappier A. A city scale degree-day method to assess building space heating energy demands in Strasbourg Eurometropolis (France). Appl Energy 2016;184:40–54. https://doi.org/https://doi.org/10.1016/j.apenergy.2016.09.075.
[111] Fazeli R, Ruth M, Davidsdottir B. Temperature response functions for residential energy demand – A review of models. Urban Clim 2016;15:45–59. https://doi.org/https://doi.org/10.1016/j.uclim.2016.01.001.
[112] Westermann P, Evins R. Surrogate modelling for sustainable building design – A review. Energy Build 2019;198:170–86. https://doi.org/https://doi.org/10.1016/j.enbuild.2019.05.057.
[113] Manfren M, Aste N, Moshksar R. Calibration and uncertainty analysis for computer models – A meta-model based approach for integrated building energy simulation. Appl Energy 2013;103:627–41. https://doi.org/http://doi.org/10.1016/j.apenergy.2012.10.031.
[114] Paulus MT, Claridge DE, Culp C. Algorithm for automating the selection of a temperature dependent change point model. Energy Build 2015;87:95–104. https://doi.org/https://doi.org/10.1016/j.enbuild.2014.11.033.
[115] Miller C, Nagy Z, Schlueter A. Automated daily pattern filtering of measured building performance data. Autom Constr 2015;49:1–17. https://doi.org/https://doi.org/10.1016/j.autcon.2014.09.004.
[116] Jalori S, Reddy TA. A new clustering method to identify outliers and diurnal schedules from building energy interval data. ASHRAE Trans 2015;121:33.
[117] Richard M-A, Fortin H, Poulin A, Leduc M-A, Fournier M. Daily load profiles clustering: a powerful tool for demand side management in medium-sized industries. ACEEE Summer Study Energy Effic. Ind., 2017.
[118] Adhikari RS, Aste N, Manfren M. Multi-commodity network flow models for dynamic energy management – Smart Grid applications. Energy Procedia 2012;14:1374–9. https://doi.org/http://dx.doi.org/10.1016/j.egypro.2011.12.1104.
[119] Dorfner J. Open source modelling and optimisation of energy infrastructure at urban scale. Technische Universität München, 2016.
[120] Manfren M. Multi-commodity network flow models for dynamic energy management – Mathematical formulation. Energy Procedia 2012;14:1380–5. https://doi.org/http://dx.doi.org/10.1016/j.egypro.2011.12.1105.
[121] Kraning M, Chu E, Lavaei J, Boyd S. Dynamic Network Energy Management via Proximal Message Passing. Found Trends Optim 2014;1:73–126. https://doi.org/10.1561/2400000002.
[122] Hilpert S, Kaldemeyer C, Krien U, Günther S, Wingenbach C, Plessmann G. The Open Energy Modelling Framework (oemof)-A new approach to facilitate open science in energy system modelling. Energy Strateg Rev 2018;22:16–25.

[123] Jentsch MFF, Bahaj ABSAS, James PABAB. Climate change future proofing of buildings—Generation and assessment of building simulation weather files. Energy Build 2008;40:2148–68. https://doi.org/https://doi.org/10.1016/j.enbuild.2008.06.005.
[124] Jentsch MF, James PAB, Bourikas L, Bahaj AS. Transforming existing weather data for worldwide locations to enable energy and building performance simulation under future climates. Renew Energy 2013;55:514–24. https://doi.org/https://doi.org/10.1016/j.renene.2012.12.049.
[125] Bravo Dias J, Carrilho da Graça G, Soares PMM. Comparison of methodologies for generation of future weather data for building thermal energy simulation. Energy Build 2020;206:109556. https://doi.org/https://doi.org/10.1016/j.enbuild.2019.109556.
[126] Stadler P, Girardin L, Ashouri A, Maréchal F. Contribution of Model Predictive Control in the Integration of Renewable Energy Sources within the Built Environment. Front Energy Res 2018;6:22. https://doi.org/10.3389/fenrg.2018.00022.
[127] Orehounig K, Mavromatidis G, Evins R, Dorer V, Carmeliet J. Towards an energy sustainable community: An energy system analysis for a village in Switzerland. Energy Build 2014. https://doi.org/10.1016/j.enbuild.2014.08.012.
[128] Orehounig K, Evins R, Dorer V. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. Appl Energy 2015;154:277–89. https://doi.org/https://doi.org/10.1016/j.apenergy.2015.04.114.
[129] Mazzoni S, Ooi S, Nastasi B, Romagnoli A. Energy storage technologies as techno-economic parameters for master-planning and optimal dispatch in smart multi energy systems. Appl Energy 2019;254:113682. https://doi.org/https://doi.org/10.1016/j.apenergy.2019.113682.
[130] Lammers N, Kissock K, Abels B, Sever F. Measuring progress with normalized energy intensity. SAE Int J Mater Manuf 2011;4:460–7.
[131] Hallinan KP, Brodrick P, Northridge J, Kissock JK, Brecha RJ. Establishing building recommissioning priorities and potential energy savings from utility energy data 2011.
[132] Hallinan KP, Kissock JK, Brecha RJ, Mitchell A. Targeting residential energy reduction for city utilities using historical electrical utility data and readily available building data 2011.
[133] Danov S, Carbonell J, Cipriano J, Martí-Herrero J. Approaches to evaluate building energy performance from daily consumption data considering dynamic and solar gain effects. Energy Build 2013;57:110–8. https://doi.org/https://doi.org/10.1016/j.enbuild.2012.10.050.
[134] Masuda H, Claridge DE. Inclusion of Building Envelope Thermal Lag Effects in Linear Regression Models of Daily Basis Building Energy Use Data 2012.
[135] Bynum JD, Claridge DE, Curtin JM. Development and testing of an Automated Building Commissioning Analysis Tool (ABCAT). Energy Build 2012;55:607–17. https://doi.org/https://doi.org/10.1016/j.enbuild.2012.08.038.
[136] Hitchin R, Knight I. Daily energy consumption signatures and control charts for air-conditioned buildings. Energy Build 2016;112:101–9. https://doi.org/https://doi.org/10.1016/j.enbuild.2015.11.059.
[137] Jalori S, Reddy TA. A unified inverse modeling framework for whole-building energy interval data: daily and hourly baseline modeling and short-term load forecasting. ASHRAE Trans 2015;121:156.
[138] Abushakra B, Paulus MT. An hourly hybrid multi-variate change-point inverse

model using short-term monitored data for annual prediction of building energy performance, part III: Results and analysis (1404-RP). Sci Technol Built Environ 2016;22:984–95. https://doi.org/10.1080/23744731.2016.1215659.
[139] Bauwens G, Roels S. Co-heating test: A state-of-the-art. Energy Build 2014;82:163–72. https://doi.org/https://doi.org/10.1016/j.enbuild.2014.04.039.
[140] Erkoreka A, Garcia E, Martin K, Teres-Zubiaga J, Del Portillo L. In-use office building energy characterization through basic monitoring and modelling. Energy Build 2016;119:256–66. https://doi.org/https://doi.org/10.1016/j.enbuild.2016.03.030.
[141] Giraldo-Soto C, Erkoreka A, Mora L, Uriarte I, Del Portillo LA. Monitoring System Analysis for Evaluating a Building's Envelope Energy Performance through Estimation of Its Heat Loss Coefficient. Sensors (Basel) 2018;18:2360. https://doi.org/10.3390/s18072360.
[142] Uriarte I, Erkoreka A, Giraldo-Soto C, Martin K, Uriarte A, Eguia P. Mathematical development of an average method for estimating the reduction of the Heat Loss Coefficient of an energetically retrofitted occupied office building. Energy Build 2019;192:101–22. https://doi.org/https://doi.org/10.1016/j.enbuild.2019.03.006.
[143] Busato F, Lazzarin RM, Noro M. Energy and economic analysis of different heat pump systems for space heating. Int J Low-Carbon Technol 2012;7:104–12. https://doi.org/10.1093/ijlct/cts016.
[144] Busato F, Lazzarin RM, Noro M. Two years of recorded data for a multisource heat pump system: A performance analysis. Appl Therm Eng 2013;57:39–47. https://doi.org/https://doi.org/10.1016/j.applthermaleng.2013.03.053.
[145] Krese G, Lampret Ž, Butala V, Prek M. Determination of a Building's balance point temperature as an energy characteristic. Energy 2018;165:1034–49. https://doi.org/https://doi.org/10.1016/j.energy.2018.10.025.
[146] Sjögren J-U, Andersson S, Olofsson T. Sensitivity of the total heat loss coefficient determined by the energy signature approach to different time periods and gained energy. Energy Build 2009;41:801–8. https://doi.org/https://doi.org/10.1016/j.enbuild.2009.03.001.
[147] Vesterberg J, Andersson S, Olofsson T. Robustness of a regression approach, aimed for calibration of whole building energy simulation tools. Energy Build 2014;81:430–4. https://doi.org/https://doi.org/10.1016/j.enbuild.2014.06.035.
[148] Meng Q, Xiong C, Mourshed M, Wu M, Ren X, Wang W, et al. Change-point multivariable quantile regression to explore effect of weather variables on building energy consumption and estimate base temperature range. Sustain Cities Soc 2020;53:101900. https://doi.org/https://doi.org/10.1016/j.scs.2019.101900.
[149] Westermann P, Deb C, Schlueter A, Evins R. Unsupervised learning of energy signatures to identify the heating system and building type using smart meter data. Appl Energy 2020;264:114715. https://doi.org/https://doi.org/10.1016/j.apenergy.2020.114715.
[150] Pasichnyi O, Wallin J, Kordas O. Data-driven building archetypes for urban building energy modelling. Energy 2019;181:360–77. https://doi.org/https://doi.org/10.1016/j.energy.2019.04.197.
[151] Abdolhosseini Qomi MJ, Noshadravan A, Sobstyl JM, Toole J, Ferreira J, Pellenq RJ-MJ-MJ-MJ-MJ-M, et al. Data analytics for simplifying thermal efficiency planning in cities. J R Soc Interface 2016;13:20150971. https://doi.org/10.1098/rsif.2015.0971.
[152] Afshari A, Friedrich LA, Liu N, Friedrich LA. Inverse modeling of the urban

energy system using hourly electricity demand and weather measurements, Part 1: Black-box model. Energy Build 2017;157:126–38.
[153] Afshari A, Friedrich LA, Liu N, Friedrich LA. Inverse modeling of the urban energy system using hourly electricity demand and weather measurements, Part 2: Gray-box model. Energy Build 2017;157:139–56.
[154] Catalina T, Virgone J, Blanco E. Development and validation of regression models to predict monthly heating demand for residential buildings. Energy Build 2008;40:1825–32.
[155] Hygh JS, DeCarolis JF, Hill DB, Ranjithan SR. Multivariate regression as an energy assessment tool in early building design. Build Environ 2012;57:165–75.
[156] Asadi S, Amiri SS, Mottahedi M. On the development of multi-linear regression analysis to assess energy consumption in the early stages of building design. Energy Build 2014;85:246–55.
[157] Al Gharably M, DeCarolis JF, Ranjithan SR. An enhanced linear regression-based building energy model (LRBEM+) for early design. J Build Perform Simul 2016;9:115–33.
[158] Ipbüker C, Valge M, Kalbe K, Mauring T, Tkaczyk AH. Case Study of Multiple Regression as Evaluation Tool for the Study of Relationships between Energy Demand, Air Tightness, and Associated Factors. J Energy Eng 2016;143:4016027.
[159] Abdelalim A, O'Brien W, Shi Z. Data visualization and analysis of energy flow on a multi-zone building scale. Autom Constr 2017;84:258–73. https://doi.org/https://doi.org/10.1016/j.autcon.2017.09.012.
[160] Liu X, Mancarella P. Modelling, assessment and Sankey diagrams of integrated electricity-heat-gas networks in multi-vector district energy systems. Appl Energy 2016;167:336–52. https://doi.org/https://doi.org/10.1016/j.apenergy.2015.08.089.
[161] Masuda H, Claridge D. Estimation of building parameters using simplified energy balance model and metered whole building energy use 2012.
[162] Manfren M, Nastasi B. From in-situ measurement to regression and time series models: An overview of trends and prospects for building performance modelling. AIP Conf Proc 2019;2123:20100. https://doi.org/10.1063/1.5117027.
[163] ISO. ISO 52000-1:2017, Energy performance of buildings — Overarching EPB assessment – Part 1: General framework and procedures 2017.
[164] Alzetto F, Meulemans J, Pandraud G, Roux D. A perturbation method to estimate building thermal performance. Comptes Rendus Chim 2018;21:938–42. https://doi.org/https://doi.org/10.1016/j.crci.2018.09.003.
[165] Meulemans J. An assessment of the QUB/e method for fast in situ measurements of the thermal performance of building fabrics in cold climates. Cold Clim. HVAC Conf., 2018, p. 317–26.
[166] Thébault S, Bouchié R. Refinement of the ISABELE method regarding uncertainty quantification and thermal dynamics modelling. Energy Build 2018;178:182–205. https://doi.org/https://doi.org/10.1016/j.enbuild.2018.08.047.
[167] ISO 52016-1:2017(en) Energy performance of buildings — Energy needs for heating and cooling, internal temperatures and sensible and latent heat loads — Part 1: Calculation procedures 2017.
[168] ASHRAE 140-2017 - Standard Method of Test for the Evaluation of Building Energy Analysis Computer Programs (ANSI Approved) 2017.
[169] Calleja Rodríguez G, Carrillo Andrés A, Domínguez Muñoz F, Cejudo López JM, Zhang Y. Uncertainties and sensitivity analysis in building energy simulation

using macroparameters. Energy Build 2013;67:79–87. https://doi.org/http://doi.org/10.1016/j.enbuild.2013.08.009.
[170] Fuentenueva C De, Naveros I, Ghiaus C, Ordoñez J, Ruiz DP. Thermal networks considering graph theory and thermodynamics. 12th Int. Conf. Heat Transf. Fluid Mech. Thermodyn., 2016, p. 1568–73.
[171] Naveros I, Ghiaus C, Ordoñez J, Ruíz DP, Ru'\iz DP. Thermal networks from the heat equation by using the finite element method. WIT Trans Eng Sci 2016;106:33–43. https://doi.org/10.2495/ht160041.
[172] Michalak P. A thermal network model for the dynamic simulation of the energy performance of buildings with the time varying ventilation flow. Energy Build 2019;202:109337. https://doi.org/https://doi.org/10.1016/j.enbuild.2019.109337.
[173] Lundström L, Akander J, Zambrano J. Development of a Space Heating Model Suitable for the Automated Model Generation of Existing Multifamily Buildings—A Case Study in Nordic Climate. Energies 2019;12. https://doi.org/10.3390/en12030485.
[174] Raillon L, Ghiaus C. Study of Error Propagation in the Transformations of Dynamic Thermal Models of Buildings. J Control Sci Eng 2017;2017.
[175] Oliveira Panão MJN, Santos CAP, Mateus NM, Carrilho da Graça G. Validation of a lumped RC model for thermal simulation of a double skin natural and mechanical ventilated test cell. Energy Build 2016;121:92–103. https://doi.org/https://doi.org/10.1016/j.enbuild.2016.03.054.
[176] Andriamamonjy A, Klein R, Saelens D. Automated grey box model implementation using BIM and Modelica. Energy Build 2019;188-189:209–25. https://doi.org/https://doi.org/10.1016/j.enbuild.2019.01.046.
[177] Lehmann B, Gyalistras D, Gwerder M, Wirth K, Carl S. Intermediate complexity model for Model Predictive Control of Integrated Room Automation. Energy Build 2013;58:250–62. https://doi.org/https://doi.org/10.1016/j.enbuild.2012.12.007.
[178] Zhao F, Lee SH, Augenbroe G. Reconstructing building stock to replicate energy consumption data. Energy Build 2016;117:301–12. https://doi.org/https://doi.org/10.1016/j.enbuild.2015.10.001.
[179] Booth AT, Choudhary R, Spiegelhalter DJ. A hierarchical Bayesian framework for calibrating micro-level models with macro-level data. J Build Perform Simul 2013;6:293–318.
[180] Lim H, Zhai ZJ. Review on stochastic modeling methods for building stock energy prediction. Build Simul 2017;10:607–24. https://doi.org/10.1007/s12273-017-0383-y.
[181] Raillon L, Ghiaus C. An efficient Bayesian experimental calibration of dynamic thermal models. Energy 2018;152:818–33. https://doi.org/https://doi.org/10.1016/j.energy.2018.03.168.
[182] Raillon LL, Ghiaus C. Sequential Monte Carlo for states and parameters estimation in dynamic thermal models. Build. Simul. 2017 Conf. (San Fr. USA), 2017, p. 988–97.
[183] Drgoňa J, Arroyo J, Cupeiro Figueroa I, Blum D, Arendt K, Kim D, et al. All you need to know about model predictive control for buildings. Annu Rev Control 2020. https://doi.org/https://doi.org/10.1016/j.arcontrol.2020.09.001.
[184] Serale G, Fiorentini M, Capozzoli A, Bernardini D, Bemporad A. Model Predictive Control (MPC) for Enhancing Building and HVAC System Energy Efficiency: Problem Formulation, Applications and Opportunities. Energies 2018;11:631.

[185] Aste N, Manfren M, Marenzi G. Building Automation and Control Systems and performance optimization: A framework for analysis. Renew Sustain Energy Rev 2017;75:313–30. https://doi.org/https://doi.org/10.1016/j.rser.2016.10.072.
[186] Ahmad MW, Mourshed M, Mundow D, Sisinni M, Rezgui Y. Building energy metering and environmental monitoring – A state-of-the-art review and directions for future research. Energy Build 2016;120:85–102. https://doi.org/https://doi.org/10.1016/j.enbuild.2016.03.059.
[187] Carstens H, Xia X, Yadavalli S. Measurement uncertainty in energy monitoring: Present state of the art. Renew Sustain Energy Rev 2018;82:2791–805. https://doi.org/https://doi.org/10.1016/j.rser.2017.10.006.
[188] Schmidt M, Åhlund C. Smart buildings as Cyber-Physical Systems: Data-driven predictive control strategies for energy efficiency. Renew Sustain Energy Rev 2018;90:742–56. https://doi.org/https://doi.org/10.1016/j.rser.2018.04.013.
[189] Bollinger LA, Davis CB, Evins R, Chappin EJL, Nikolic I. Multi-model ecologies for shaping future energy systems: Design patterns and development paths. Renew Sustain Energy Rev 2018;82:3441–51. https://doi.org/https://doi.org/10.1016/j.rser.2017.10.047.
[190] Pfenninger S, DeCarolis J, Hirth L, Quoilin S, Staffell I. The importance of open data and software: Is energy research lagging behind? Energy Policy 2017;101:211–5. https://doi.org/https://doi.org/10.1016/j.enpol.2016.11.046.
[191] Pfenninger S, Hirth L, Schlecht I, Schmid E, Wiese F, Brown T, et al. Opening the black box of energy modelling: Strategies and lessons learned. Energy Strateg Rev 2018;19:63–71. https://doi.org/https://doi.org/10.1016/j.esr.2017.12.002.
[192] Deane JP, Chiodi A, Gargiulo M, Gallachóir BPÓ. Soft-linking of a power systems model to an energy systems model. Energy 2012;42:303–12.
[193] Dominković DF, Junker RG, Lindberg KB, Madsen H. Implementing flexibility into energy planning models: Soft-linking of a high-level energy planning model and a short-term operational model. Appl Energy 2020;260:114292. https://doi.org/https://doi.org/10.1016/j.apenergy.2019.114292.
[194] Zafar R, Mahmood A, Razzaq S, Ali W, Naeem U, Shehzad K. Prosumer based energy management and sharing in smart grid. Renew Sustain Energy Rev 2018;82:1675–84. https://doi.org/https://doi.org/10.1016/j.rser.2017.07.018.
[195] Zepter JM, Lüth A, Crespo del Granado P, Egging R. Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage. Energy Build 2019;184:163–76. https://doi.org/https://doi.org/10.1016/j.enbuild.2018.12.003.
[196] Sioshansi FP. Consumer, Prosumer, Prosumager: How Service Innovations Will Disrupt the Utility Business Model. Academic Press; 2019.
[197] Hardin D, Stephan EG, Wang W, Corbin CD, Widergren SE. Buildings interoperability landscape. 2015.
[198] Atzori L, Iera A, Morabito G. The Internet of Things: A survey. Comput Networks 2010;54:2787–805. https://doi.org/https://doi.org/10.1016/j.comnet.2010.05.010.
[199] Tan L, Wang N. Future internet: The Internet of Things. 2010 3rd Int. Conf. Adv. Comput. Theory Eng., vol. 5, 2010, p. V5–376 – V5–380. https://doi.org/10.1109/ICACTE.2010.5579543.
[200] Breiner S, Subrahmanian E, Sriram RD. Modeling the Internet of Things: A Foundational Approach. Proc. Seventh Int. Work. Web Things, ACM; 2016, p. 38–41.
[201] Reka SS, Dragicevic T. Future effectual role of energy delivery: A

comprehensive review of Internet of Things and smart grid. Renew Sustain Energy Rev 2018;91:90–108. https://doi.org/https://doi.org/10.1016/j.rser.2018.03.089.
[202] Arghandeh R, von Meier A, Mehrmanesh L, Mili L. On the definition of cyber-physical resilience in power systems. Renew Sustain Energy Rev 2016;58:1060–9. https://doi.org/https://doi.org/10.1016/j.rser.2015.12.193.
[203] Andoni M, Robu V, Flynn D, Abram S, Geach D, Jenkins D, et al. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew Sustain Energy Rev 2019;100:143–74. https://doi.org/https://doi.org/10.1016/j.rser.2018.10.014.