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Open data and energy analytics - An analysis of essential information for energy system planning, design and operation

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ABSTRACT

Energy transitions are reshaping global and national energy systems and appropriate decision-making strategies are needed to drive an effective change in response to pressing global issues. Governmental institutions, industry, academia, and civil society are all participating to this global change, playing different roles. Open energy models and associated data are essential to promote open science practices, and create an effective science-policy interaction. For example, they can foster multi-disciplinary research addressing the co-evolution of energy technologies and human behaviour more transparently and, more in general, they can improve the interaction of multiple linked models and data, by improving them with respect to the current state of the art. In this paper, we present an analysis of features of open energy models and data, highlighting essential information that can be shared among communities of researchers in the energy field to foster multidisciplinary research. This information inherently embodies different key concepts and perspectives in modelling that affect both simulation and optimization processes employed for energy systems planning, design and operation. Indeed, this shared knowledge is crucial to overcome critical technical issues (e.g. end-use energy efficiency improvements, energy conversion processes, energy infrastructures operation, etc.) that may inhibit successful energy transitions. Finally, ecosystems of interacting open data and models are key assets for the development of next generation energy services and technologies, based on innovative business models in which the problem of monitoring, verifying and tracking performance transparently (at multiple levels) will be fundamental.

1. Introduction

Decentralization, digitization and innovative business models are essential drivers in energy transitions, which will affect energy systems at multiple levels. Open data, open science, open innovation and open energy modelling principles are crucial to create an effective science-policy interaction, because governmental institutions, industry, academia, and civil society will need to interact in multiple ways in transition processes [1–3]. A relevant research effort has been devoted in recent years to conceptualization of sustainability transitions [4] and, more specifically for energy, it is crucial today to conceptualize “complementarities” at multiple levels [5] and to adopt a multi-level perspective in planning low carbon transitions [6,7]. In particular, if we have to address the general topic of the co-evolution of human behaviour, energy technologies, infrastructures and, at the same time, we have to tackle specific problems and applications coherently, (i.e. if we have to answer specific research question while following the above mentioned general principles), we need to define a clear conceptual framework for our research and understanding the inherent “complementarities” embodied by different perspectives in energy modelling for systems planning, design and operation. This problem constitutes essentially the motivation of the research presented in this paper, which aims to highlight links among some of the key concept in energy research at the state of the art and propose an interpretation of emerging concepts that can be relevant for the future development of ecosystems of interacting applications, using open data and open models. Open data and models may represent a key asset for the development of next generation energy services and technologies, which will have to be based on innovative business models in which the problem of monitoring, verifying and tracking performance improvements in a transparent

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way will be fundamental. Clearly, the availability of data at multiple levels will be an enabling factor and infrastructures and technologies such at the Internet of Things (IOT) [8] and cyberphysical systems are essential for disruptive innovations in the energy sectors regarding, for example, built environment [9], energy delivery to end users [10] and energy infrastructures [11]. As already mentioned, innovative business models will have a relevant role for the evolution of the energy systems, considering concepts such as prosumer [12] and prosumager [13]. We believe that all the elements reported before have to be considered when pursuing research aiming at radical shifts in energy systems, coherent and consistent with sustainability transition strategies.

1.1. Background and motivation

Energy transitions involve the evolution of the network of actors and groups that are traditionally operating in the energy sector (e.g. policy makers, regulatory authorities, transmission and distribution authorities, etc.). Indeed, socio-technical innovations depends critically on the possibility to access new information, knowledge, and resources which, in turn, are key enablers for the development of new ideas and products [14]. We can find in innovation studies the concept of multi-level perspective (MLP) [6], which is one of the basic elements of socio-technical transition strategies [15,16], where MLP concept can be used to critically question current "regime" level [7]. In fact, MLP analytical process articulates in three levels: niches (where socio-technical changes are introduced and tested), regime (where technologies, institutions and practices are aligned and conformed) and landscape (context for regime stability or change). Simply put, the scope of MLP is that of enabling niche experiments to scale-up and change the regime, exploiting external pressures. Pressures include, for example, opportunities that may emerge also at the local level [17]. Further, innovation intermediaries can help accelerating environmental sustainability transitions [18], leading to the creation of business ecosystems in sustainability transitions. For this reason, we will illustrate hereafter some of the most relevant elements for the creation of business ecosystems in sustainability transitions. First of all, the achievement of stringent energy efficiency goals is one of the crucial elements in energy transition strategies and, more in general, in sustainability transitions. Energy efficiency measures are designed to provide benefits in terms of energy, emission and cost savings, but other related co-benefits can be present as well (e.g. improved indoor environmental quality, health, productivity, pollution reduction etc.). While the concept of Energy Performance Contracting (EPC) is not new, the potential of energy efficiency measures is still largely untapped. For this reason, it is necessary to rethink critically the structure of EPC, by understanding better the role of relevant actors, stakeholders and coalitions [19] and by engaging them appropriately, considering barriers such lack of interest, awareness, knowledge and human and financial capacity [20]. Additionally, the role of consumer in the energy sectors has experienced an important evolution in recent years going from consumer, to prosumer and to prosumager [13]. In order to secure the expected savings, performance has to be monitored, verified and tracked transparently. Today, this can happen by means of automated or semi-automated data analysis workflows [21], using state of the art computing technologies and the Internet of Things [10]. Rather than being conceived for separate applications, we can envision ecosystems of applications [22] based upon open data and models [23,24], which may be linked to innovative business models to determine techno-economically feasibile paths in sustainability transitions. These ecosystems can be represented by groups of interconnected applications that are aimed at supporting energy transitions. Applications can share a set of common features and information, to ensure the standardization of methods and consistency with open science principles. Following these arguments, in Section 2 we will describe some elements emerging from research on open energy data and models, highlighting a possible path from open energy modelling principles to systems of interacting models. Then, in Section 3 we will analyse essential features of systems of models from a theoretical perspective, highlighting useful features. After that, in Section 4 we will present some examples of applications that may benefit from an evolution towards systems of models. Finally in Section 3 we summarize the most relevant concepts and insights to set questions for future research.

2. From open energy modelling principles to systems of models

Looking at recent research, we can extract some interesting principles that may contribute to reshape energy research profoundly, from a methodological point of view, in the near future. We describe these principles going from open energy modelling to systems of models, even though the elements reported are not strictly sequential (they have been proposed by different authors at different point in times and in different contexts), as we clarify in Fig. 1.

First, we need to recall the fact that we are still far from exploiting the real potential of open data and analytics for energy systems [23], even though there are extremely important initiatives on open energy modelling [25] and data analytics [26], where transparency is an essential component [24,27]. The choice of a modelling paradigm can be debatable [28], as well as the specific rules adopted within a specific modelling paradigm [29].

Further, we have to acknowledge clearly the limitations of individual models and eventually find ways to "soft-link" them [30] being aware of their limitations (that determine boundaries of acceptability for their application), but also of the possibility to use them at multiple scales for informed decision-making [31]. Transparency of modelling can be considered as a pre-requisite for "soft-linking" and the ability to integrate data and information from multiple sources (and bottom-up and top-down perspectives as well) is inherently fundamental for the complex interdisciplinary research on sustainability transition pathways [4] and, more

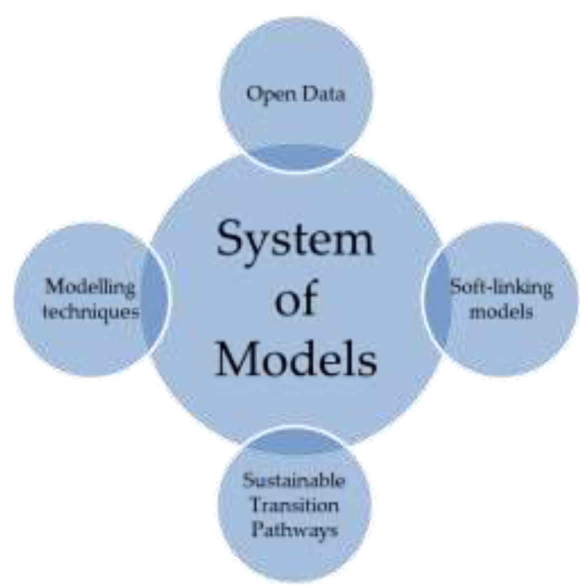

Fig. 1. From open energy modelling principles to systems of models.

specifically, for the analysis of complementarities in energy transitions [5]. In principles, elements emerging from recent research highlight the necessity of a structured approach to systems of models (e.g. multi-model ecologies [22]), in order to engineer complex networked systems [32] that have to evolve on a continuous base because they are part of a fast-evolving socio-technical landscape. We can give some examples of specific problems that depend on the interaction of technologies (at multiple levels) and on human behaviour. First of all, the "performance gap" problem in the built environment, regarding not merely direct energy use [33,34], but also embodied energy use and emissions [35], highlighting the intrinsic limitations of current approaches to sustainability [36,37]. Further, the necessity of finding paths of integration of technologies (in the built environment in particular [38]) to achieve decarbonisation and energy flexibility goals. Additionally, with respect to decentralized energy infrastructures, the optimization of multi-energy systems [39,40] that can be represented as multi-commodity networks [41–44]. After that, the use hydrogen and innovative energy carriers [45], that are an essential component of multi-energy systems, and are an enabling technology for long-term storage and CO_2 recycling [46]. These are just some of the current issue in energy research that will be described in more detail in Section 5 by means of examples.

3. Systems of models – analysis of essential information and features

In the previous section we highlighted some principles that can help creating a framework for future research in the area of systems of energy models. We can find in recent literature examples of thorough analysis of open data and systems of models [23–25,27], and one of them using the specific term of "multi-model ecologies" [22]. In this paper, the authors insist on three key concepts: connectivity, diversity and hierarchy. In this research we will use these definitions as a basis and we will concentrate first on connectivity and diversity (Section 4.1), and then we will highlight some essential features and information (Section 4.2) that may help defining a clear hierarchy (i.e. structure and organization) of systems of models, with some examples from built environment research. In Fig. 2 we report the three concepts defining systems of models and we highlight the importance of modelling standards and cyber-physical systems and IoT infrastructure as enabling factors for their deployment.

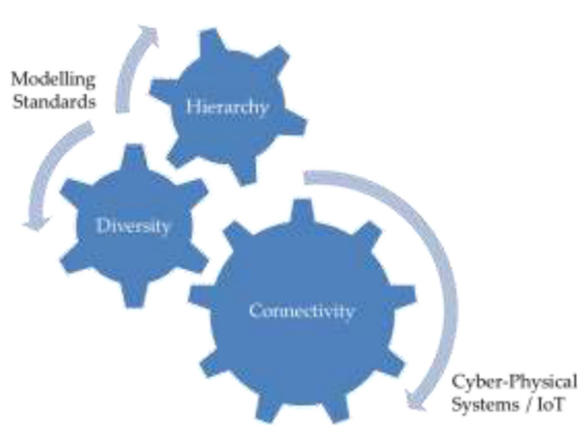

Fig. 2. Systems of models – Connectivity, diversity, hierarchy.

3.1. Connectivity (and interoperability) and diversity in systems of models

Connectivity involves increasing the ability to exchange data, information and knowledge among different models, datasets and actors involved in the use of models (either directly or indirectly, encompassing, more in general, the communication channels which facilitate the flow of information and knowledge). Therefore, connectivity is intertwined deeply with interoperability, which aims to ease the flow of data and information among different types of applications. On the other hand, diversity is crucial as well, as we need to cope with the increasing complexity of energy systems, where technical factors and social factors become interdependent [4,5] (i.e. we need to coordinate hierarchically the use of multiple models that are interdependent and that have to co-evolve). Meta-modelling (or surrogate, reduced-order modelling) concept [47,48] may be introduced as a tool to find a balance between connectivity and diversity needs in systems of models. In fact, meta-models represent simplifications of more complex models that embody relevant advantages from the computational point of view (e.g. reduction of computing time and resources) but also from the interoperability point of view (e.g. use of open standards for software). Indeed, we can trace a parallel between this research and more general purpose research on modelling for IOT/cyber-physical systems, using standardized principles and rules [8], independently on the specific field of application.

3.2. Hierarchy and integration of essential features and information for energy system planning, design and operation

We portrayed in Section 2 some recent advances in energy research, highlighting a possible path of evolution going from open energy modelling principles to systems of models. It is very important to think forward and to try to anticipate how these emerging principles will contribute to reshape research on energy technology and energy systems planning, design and operation. In this Section we will propose some essential features and information that could be at the basis of future developments of modelling research targeted to the creation and deployment of models in IOT/Cyber-physical systems in an integrated and hierarchical way, following the principles indicated in literature [8,9,22–24]. Fig. 3 depicts these essential features.

We introduced previously the concept of meta-modelling, i.e.

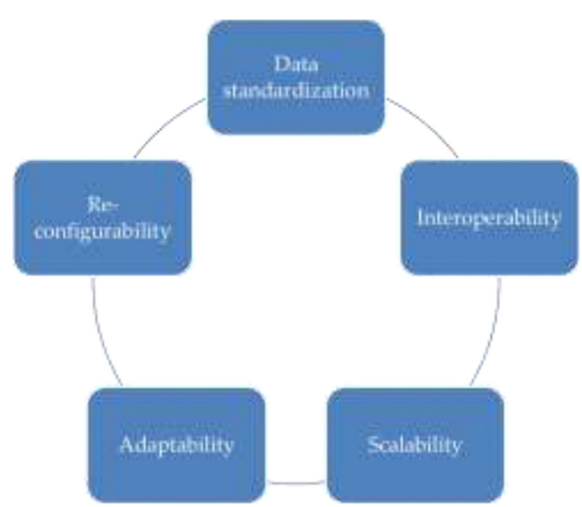

Fig. 3. Essential features of system of models.

surrogate modelling, as an essential tool to reach a compromise between diversity and interoperability of models, and to be able to exploit current standardization in modelling and communication protocols. Additionally, we can think about models as “digital twins” (i.e. digital counterparts) of real world processes, giving the possibility to use data analytics to improve the performance of services and technologies by exploiting multiple feedback loops. We can find examples of the use of meta-modelling techniques to face problems at multiple scales in the built environment, from individual buildings and facilities [49], to urban scale [50], to regional scale and geographic clusters [51]. These examples present several conceptual analogies with previous research on the use of meta-modelling concept for integrated building performance analysis [47]. The application of these principles at multiple scales can be targeted, for example, to problems such as the decarbonisation of building stock [52–54], as well as many other problems that will be reported in Section 4. We believe that the development of innovative technologies and services for energy transitions could benefit from the features proposed hereafter that we summarize in Table 1, contextualizing with respect to built environment research, and we provide a graphical diagram in Fig. 4 representing a potential path of development from open energy modelling principles up to systems of models and their essential features.

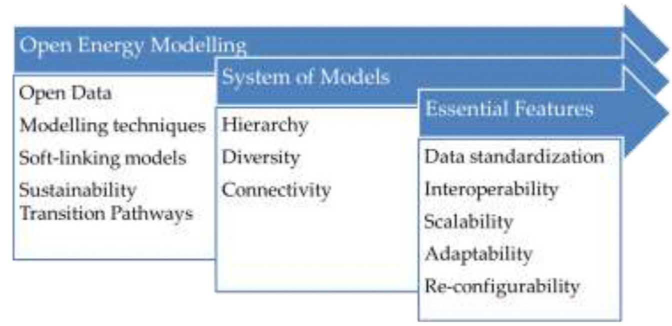

Fig. 4. Potential path of development from open energy modelling principles up to systems of models and their essential features.

4. Systems of models – examples from current research

In Section 3 we introduced essential features and information for systems of models that can be built upon open energy modelling principles. In this Section we will present examples of application that can benefit from an evolution of research in the direction of systems of open models. Recalling some of the concepts introduced in Section 2, the examples are organized as follows. First, we describe energy modelling problems at multiple levels in the built environment. After that, we describe issues related to electrification of heating and transportation and their impact on energy infrastructures. Finally, we discuss issues related to multi-energy systems, innovative energy carriers and storage, which are fundamental for low carbon and decentralized energy systems design and operation.

4.1. Multi-level energy modelling in the built environment

In the last years comprehensive reviews of building energy models [97–99] have been published. A comprehensive analysis of energy performance of buildings requires understanding both the human and technical influencing factors [100]. These factors can create a discrepancy between design and measured performance, i.e. a performance gap [33,101]. In order to enable large scale performance benchmarking for buildings, it is necessary to introduce the concept of statistical “Reference Buildings” [102], i.e. building models that represent the common typologies, technologies and end-uses in the building stock, identified by means of statistical analysis. For this reason, the identification of Reference Buildings requires the use of large scale statistical data. However, building data are generally multi-level data, making it difficult to have access to the complete information at scale. Nonetheless, a statistical approach to building performance [103] is necessary to reconcile bottom-up and top-down perspectives in energy modelling [97] and to create a soft-linking among different energy models, applied at multiple scales. The use of Reference Buildings is common today, for example, for techno-economic optimization of buildings using methods such as cost-optimal analysis [102,104], for utility scale performance analysis of design [105] and operation [53] strategies and for energy planning at national scale [106–108]. Further, more advanced techniques such as Bayesian analysis could be used to reconstruct built environment data under uncertainty [109–111].

Table 1
Essential features for models – Examples from built environment research.

Feature	Description	Examples	Research advances
Data standardization	Standard data formats	Building Information Modelling (BIM) [55], Energy performance of buildings [56], Common Data Environment (CDE) [57–59], City Geography Markup Language (CityGML) [60,61]	Future research efforts could be devoted to the creation of flexible data standard, starting from linked open data concept
Interpretability	Increased transparency	Visualization of energy/exergy flow across multiple levels in systems [62] and in buildings [63]. Operational profiles visualization [64]	Visual analytics can help achieving more transparent and intuitive comparisons of models results, at multiple levels of analysis
Scalability	Spatial scalability	Building fabric [65–68], whole building [69–71], building stock [53,72], community and city scale [73,74]	Models can be developed with multiple spatial resolutions, increasing progressively the level of detail
	Temporal scalability	Monthly [75–79], daily [69,71,80–83], hourly interval data [84,85]	Models can be developed with multiple temporal resolutions, using an incremental approach
Flexibility/adaptability	Multiple scopes/uses	Design optimization [86–90] Energy management [69,71], Anomaly detection [70], Control [91], Monitoring of internal conditions [92,93]	Models with similar characteristics can be used for multiple purposes (e.g. multivariate regression and autoregressive models with exogenous inputs for time series)
Re-configurability	Re-configurability across life-cycle phases	Linking design and operational performance analysis [94,95]. Performance Gap analysis from design to operation [96].	A continuity in the use of models across life cycle phases of buildings/facilities or individual technologies can be established. This enables a “digital twin” approach

An interesting research development concerns physical-statistical modelling approaches that are a combination of simplified physical models and statistical computing techniques. They are generally indicated with the term “grey box” models [112]. In this type of models, physical parameters are expressed with lumped quantities (thereby reducing the amount of parameters) and the model structure represents a reduction of a detailed “white-box” physical model. In fact, models for building energy performance prediction can be roughly classified as “white-box” (detailed models), “grey-box” (physical-statistical reduced-order models) and “black-box” (statistical and machine learning reduced-order models). “White-box” models are generally detailed models based on physical laws (validated according to energy simulation test standards [113,114]) which are used for design phase simulations, while “black-box” models are used in data analysis workflows, for example in energy management during operation. In synthesis, physical-statistical models are a good comprise between the generalization capability of “white box” models and the statistical capabilities and computational efficiency of “black box” models, which however need to be trained on data. Additionally, physical-statistical models can be used both for simulation (forward mode) and system identification (inverse mode). In particular, they can derived in a transparent way from fundamental energy analysis principles [115,116] and can be thought as a starting point to create “black-box” statistical models for specific applications [117]. In terms of practical applications, they can be used to characterize the behaviour of technologies in experimental test-facilities [118]. Further, they can be integrated in the design process using Building Information Modelling (BIM) software [112]. Finally, they can be used for advanced integrated room automation [119]. Considering all these characteristics, “grey-box” models are suitable for implementation in cyberphysical systems [10]. Among others, regression-based approaches present a relevant potential for practical applications [120], in which the exploitation of the approximated physical interpretation of regression model coefficients [54,65,121,122] is essential. Indeed, the possibility of deriving an interpretation depends on the formulation of an approximated physical model used as a basis for the regression; this can be created, for example, using definitions compatible with current technical standardization [56]. In terms of practical applications, regression-based approaches could be used, for example, for heat loss coefficient (HLC) estimation [66,68,123], for projections about energy consumption in future climate change scenarios [124–126] and for creating load profiles when designing decentralized energy systems from buildings [127] up to community scale [41,128,129], linking them ideally to the many of issues described in Section 4.2 and 4.3. Further, in terms of technologies, regression-based approaches can complement the analysis of performance of heat pumps and cooling machines [130,131], considering also exergy balance [132,133], where temperature dependence is fundamental (external air temperature is the fundamental independent variable in regression [70,71]). Finally, based on their characteristics they can help providing suitable evidence of the impact of technologies [123,134] and especially efficiency measures [135], which can inform decision-making processes and future policies by means of robust and empirically grounded methods [136]. As a conclusion, the research developments presented in this Section are deeply intertwined with technological development in sensors and automation fields. The availability of building energy and environmental monitoring data, using state of the art technology [137], is a precondition for further developments regarding multi-level energy modelling in buildings, which can help improving the performance of envelope technologies [67] and HVAC systems [138]. The appropriate level of detail in modelling (going from “white-box” to “black-box” approaches) depends again on the specific application and uncertainty in measurement has to be carefully considered [139].

4.2. Load shapes analysis and electrification of heating and transportation

The co-evolution of energy infrastructures and built environment is crucial to ensure the long-term sustainability of energy services. In Section 4.1 we reported examples of analysis of data at multiple levels in the building system and at multiple scale for the building stock. In this Section we will introduce other examples where shared data are relevant for the co-evolution of energy infrastructures and built environment, considering in particular, the impact of technologies such as heat pumps, for the electrification of heating demand, and electric vehicles, for the electrification of transportation demand. First of all, we have to recall the fundamentals of electrical system engineering and economics [140], and consider load shape analysis methodologies (e.g. peak demand, load factor, coincidence factor and diversity factor, load duration curves, etc.) [141]. The analysis of load shape characteristics and temporal variability assumes today an important role because of the increasing quantity of renewable generation in the system, on the one hand, and the necessity to differentiate tariffs depending on end-uses and behaviour [142], on the other hand. The goal is that of reshaping the demand (e.g. demand response) [135] and harmonizing the methods to quantify the impact of energy efficiency investments, which are clearly dependent of energy savings actually obtained by end-users. In recent years, there have been important research initiatives in this direction such as the Uniform Methods Project [136], whose goal was to harmonized the methods for quantifying energy savings for specific measures, both in residential and commercial buildings. Rather than being simply applicable to the building sector, harmonized methods are fundamental also for system level research and policy, for example if we consider the issue of comparing simulations and measured data for large scale studies. In this sense, we can find studies aimed at synthesising electrical demand profiles for UK dwellings [143] and quantififying diversity of residential electricity demand [144]. Further, we can find examples of bottom-up modelling approaches to quantify the variability of the impact of users on load profiles at building scale [145] and the related consequences on low voltage grids [146]. Again, regarding large scale studies, the level of temporal and operational detail is fundamental also for energy-system planning models, where “traditional” optimization approaches are no longer sufficient and multiple operating configurations can be studied by binning data of loads and renewable generation [147]. If we focus on the large scale impact of heat pump technology in electric systems [148], we can find examples of field trials [149] and studies regarding the effects of decarbonisation of gas and electricity supply [150] at national scale. The penetration of heat pumps is crucial for the decarbonisation of the heating sector [151], together with district heating systems [152] and energy efficiency measures, in the built environment in particular [54]. The switch from fuel-based heating systems (e.g. natural gas) to electric heat pumps depends critically on the rate of substitution of heating technologies and will have a relevant impact on electric infrastructures, together with electrification of transportation, as mentioned before [153]. Further, power to heat concept (linking heating and electricity sector), may open up new perspectives with respect to flexibility in electric infrastructures [154] but will have also relevant implications for transmission expansion [155]. Energy flexibility is the ability to manage demand and generation according to climate, user needs and grid conditions [156]; different options exist for system level flexibility planning [157]. Flexibility in buildings depends on the capability to use storage resources and to act on appliances (including HVAC), following a trigger (e.g. time, power, energy price, etc.). Due to the inherent complexity, we can understand how demand side flexibility [156], will have to be investigated in detail in the future, regarding in particular the role of HVAC as an active part of energy infrastructures (e.g. for demand response) [158] and also as a mean to absorb surplus renewable in future energy systems with high penetration of renewables [159]. In terms of data, a high spatial and temporal resolution of models (discussed in Section 4.2) is needed to explore the potential of heating demand side management due to heat pump diffusion at scale [160], and there exist already examples of large-scale demand response provided by residential heat pumps [161]. The exploitation of distributed energy resources requires the integration of technologies such as photovoltaics, heat pumps and energy storage at the building or facility level [162]. The evolution of standardization of infrastructures communication protocols is necessary to ensure efficient operation [163]. The research on control plays an essential role for this integration in the built environment [127] and the results can be relevant for changes at the level of electric energy system as a whole [164], which may be pushed by consumer centric innovations in business models [165]. A large part of research at the state of the art concentrates on strategies to unlock the flexibility potential by means of control [166] and, for this reason, different modelling strategies have to be tested [167], considering also appropriate levels of modelling complexity [168]. As anticipated, beyond heating demand electrification, another fundamental issue is constituted by transportation demand electrification [169], which will have an impact both on building stock and distribution grids [170]. Demand side energy policies and participation are necessary to address this change [171], because of the socio-technical dimension of the problem, which requires a clear segmentation of the data regarding end-users [172]. Projections of the increase of electric demand due to transportation and change in load profiles can be determined using travel survey data [173] and tested using empirical data from selected samples of end users [174]. Indeed, projections of load profiles can be important for integrated energy planning at the urban and community scale [175,176], where the behavioural aspect of the interaction of end-users with the urban environment have to be taken into account. More in general, for the long-term evolution of energy systems and especially for built environment, electrification will be crucial [177] to tackle the decarbonisation problem, as reported before.

As a conclusion, in this Section we summarized some of the concepts emerging from energy research in the built environment (i.e. heat pumps, heating demand electrification, electrification of transportation, decarbonisation, flexibility and control). An appropriate spatial and temporal resolution of data and models, together with harmonized methodologies could help promoting multi-disciplinary research aimed at energy system planning, design and operation. While sharing the same fundamental problem of addressing the change of load profile shapes and their spatial and temporal aggregation, different research applications require specific contextual data; nonetheless further research efforts can be put in the definition of harmonized accounting methods, aimed at documenting transparently the impact of different technologies, following the examples of recent research projects [135,136]. Finally, energy (and exergy) flows can be visualized at multiple scales [62], not simply for national scale energy models but also for integrated electricity-heat-gas networks in multi-energy systems [178] or in complex building system design and operation analysis [63].

4.3. Multi-energy systems, innovative energy carriers and storage

In Section 4.1 we described some of the potential developments regarding multi-level energy modelling in the built environment, while in Section 4.2 we presented issues related to energy load shapes analysis, with a particular focus on electrification of heating and transportation. In this Section we will report examples of modelling approaches and issues concerning innovative solution for decentralization of energy infrastructures, namely multi-energy systems [178,179], energy-hubs [180–182] and microgrids [183–185]. In a decentralized perspective, the complexity of issues to be considered for optimal design and operation of buildings increases, because end-users are not simply “consumers” but “prosumers” (producers/consumers) [186]. First of all, the appropriate aggregation of demand at the community scale is a challenging problem [187], because of the necessity to provide multiple energy services and carriers for end-uses in an optimized way. Further, contingent regulations, incentive schemes and policies can have a relevant impact both on the choice of technologies [188] and energy carriers [189]. Additionally, the availability of data regarding performance and cost of technologies is fundamental, but the situation is jeopardized, following rules set by each Region and/or Country [190]. The evolution of the heating sector [191] and, in particular, the electrification of heating reported in Section 4.2, will have a relevant impact on decentralized energy systems. In fact, while at present electricity demand is still mostly dependent on the use of electrical appliances and lighting [192], heating and domestic hot water (DHW) demands can be supplied with different solutions (beyond conventional gas boilers) such as electric or gas absorption heat pumps, solar thermal [193] (eventually combined with heat pumps [194]), biomass boilers/stoves, combined heat and power or district heating systems [195]. For this reason, an energy analysis simply focused on the demand side of the problem (i.e. the calculation of a load and basic sizing criteria) is not sufficient anymore [98] because of the technological evolution of technical systems in buildings, which include distributed generation, in particular solar technologies [196]. The presence of storage and, consequently, the availability of a certain degree of inertia in the system is essential to achieve flexibility (topic introduced in Section 5.2) but creates difficulties when modelling the dynamic energy behaviour. Thermal storage in buildings depends first on the thermo-physical properties of construction components that could help modulating the operation of heating and cooling systems [197]. Further, thermal storage is generally present in building technical systems (e.g. water tanks for DHW and/or heating system) and in district energy systems [198]. The combined effect of multiple storage resources determines a relevant flexibility potential at the district scale [199]. However, the presence of storage capabilities at multiple levels increases the need for sophisticated dynamic models [200]. Additionally, the appropriate consideration of coincidence factor of loads (e.g. heating and DHW) for aggregation of users, together with storage capabilities, could determines relevant savings regarding sizing of technical systems (i.e. avoiding over-sizing). From an economic perspective, the presence of a dynamic price of electricity [201] increases further the level of complexibility of modelling, because of the need to account for the time-varying economic impact of energy demand when performing optimization. For example, load reduction and load shifting strategies are deeply influenced by the pricing schedules adopted by utilities [202]. In brief, the variations of electricity prices could be a determining factor [203] when performing techno-economic optimization (both for design and operation), in many cases even more relevant than the variations of performance of technological components themselves [204]. In turn, research advances related to predictive control of decentralized systems depends critically on the availability of forecasting of electricity prices [205], load shapes [206] and weather data, especially solar energy [207]. Additionally, the resolution of data (i.e. from yearly to hourly and sub-hourly) for emission factors can influence the results of modelling for decarbonisation strategies [208]. The definition of appropriate boundaries for energy and carbon accounting for buildings [209] is necessary to progress further with respect to zero energy and carbon neutrality concepts [210]. The issues related to end use energy demand and transportation [211] (introduced in Section 4.2) can play a relevant role in the design choices regarding microgrid control [212] and polygeneration technologies [213], especially with respect to the portfolio of fuels, where hydrogen could become an option for transportation [214]. Among other things, the valorization of process wastes or handling renewable production excess is essential both for energy efficiency and flexibility (e.g. dampening the renewable intermittency problems and performing peak shaving). Finally, the evolution of market and technology of electric energy storage [215] will play a relevant role on the optimal sizing for distributed generation systems for end-users [216], with innovative business models aimed at cost-optimality [217].

5. Summary of research findings and indications for further research

In this research work we discussed the role of open data and models for energy planning, design and operation. Fundamentally, our goal was highlighting essential information that can be shared in order to create systems of interacting models that could, in turn, enable innovative applications in energy transitions. For the reasons described in Section 2, these systems of models could represent a step forward in energy research and they could embody concepts and principles at the state-of-the-art such as open energy modelling (i.e. transparency, reproducibility, etc.) and soft linking (i.e. addressing limitations, defining boundaries for the application of models, etc.). Further, they could help creating an integration between top-down and bottom-up modelling perspectives. In Section 3 we moved from principles to specific features and information for systems of models. We started by analysing the definitions given in recent literature regarding “multi-model ecologies” [22], namely diversity (of disciplines, applications, perspectives and system scales), hierarchy (different levels of interacting models and dataset), and connectivity (exchange of data, information and knowledge among different models, datasets and actors involved). With respect to hierarchy, in Section 3.2 we proposed some essential features for models, namely data standardization, interpretability, scalability, flexibility/adaptability, re-configurability. For these features we reported in Table 1 literature examples and we indicated research advances, with a focus on built environment applications. In synthesis, these features could be the basis for future developments of modelling research targeted to the creation and deployment of models in IOT/Cyber-physical systems as “digital twins” of real-word processes. Rather than being conceived for individual and separate applications, “digital twins” can be conceived in an integrated and hierarchical way, following the principles outlined before. We believe that modelling research developments in this direction could help responding to critical issues. We gave examples in this sense in Section 4, starting from energy modelling in the built environment in Section 4.1, where we showed how “white-box” modelling approaches can be combined with “grey-box” and “black-box” statistical approaches in order to address multiple issues related to building energy performance, from design to operation, maintaining a certain degree of continuity in the data analytical workflow. After that, we discussed in Section 4.2 the possibility to analyse building energy performance at scale, in order to address challenges such as electrification of heating and transportation, which will affect the shape of load profiles in electrical systems. Finally, in Section 4.3 we described the role of models in innovative decentralized energy paradigms (i.e. multi-energy system, microgrids, energy-hubs, etc.) where the evolution of storage technologies and innovative fuels will be necessary to increase further the penetration of renewable energy source in the future.

In this research study some “transversal” topics are emerging as well. First of all, data accessibility. The problems of lack of detailed data or insufficient reliability of data due to non standardized collection procedures must be faced. Currently, it causes a knowledge gap undermining informed choices for policy making in the energy transition process (as well as in many other processes). Further, the availability of open data repositories regarding technologies, energy demand for end uses and weather data will be crucial. Having standardized and up to date data will enable consistent modelling processes at multiple levels and/or scales of analysis, reducing partially the modelling effort and pushing forward the development of next generation energy technologies and services, based on innovative business models. Finally, models' validation process. Validation is considered generally the first step when introducing a new model and this could become difficult when dealing with systems of models. The use of basic principles (e.g. energy and mass balance equations, conversion factors, etc.) and the visualization of energy flows at multiple levels in systems are crucial to make models transparent and easy to interpret, unhiding the “ad-hoc” assumptions and simplifications that are generally introduced in specific problems or applications.

6. Conclusion

In this paper we illustrated a reflection on some of the most promising principles and concepts emerging from recent energy systems research, indicating how they can contribute to the evolution of energy technologies and services, fostering multidisciplinary research. After having identified the principles, we extracted essential features and information that can be shared among communities of researchers in the energy field to overcome critical technical issues that may inhibit successful energy transitions. Far from being exhaustive, our research represents an exploratory work aimed at orienting future research efforts. Nonetheless, the research works described can provide an empirical ground and evidence to inform research regarding systems of interacting models. What we consider of particular importance, at this stage, is identifying a coherent conceptualization for the research itself. Further, we would like to explore in the future other related issues such as linking transparently advanced applications with fundamental knowledge, in order to improve transparency and reproducibility. Another aspect of future research may be that of understanding to what extent features and information are actually constraining the choice of modelling techniques in practical applications. Indeed, this type of research could determine a profound methodological innovation, by looking at the whole life-cycle of models (i.e. from feasibility, to design and operation) in relation to energy technologies and systems, where they could act as “digital twins” of real world processes.

As a conclusion, we believe that open data, open science, open innovation and, more specifically, open energy modelling principles are crucial to create an effective science-policy-market interaction in energy and sustainability transitions. Research efforts in energy modelling should be oriented to the identification of solutions that represent good compromises between connectivity and diversity and to the definition of appropriate hierarchies of data and models, for example by using linked open data schema and meta-models.

CRediT author statement

Massimiliano Manfren: Conceptualization, Methodology, Data curation, Supervision, Writing- Original draft preparation, Writing- Reviewing and Editing. **Benedetto Nastasi:** Data curation, Investigation, Visualization, Writing- Original draft preparation, Writing- Reviewing and Editing. **Daniele Groppi:** Data Curation, Investigation. **Davide Astiaso Garcia:** Data curation, Investigation, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Carayannis EG, Campbell DFJ. Mode 3 knowledge production in quadruple helix innovation systems: 21st-century democracy, innovation, and entrepreneurship for development. New York: Springer; 2011.
[2] Barrie J, Zawdie G, João E. Leveraging triple helix and system intermediaries to enhance effectiveness of protected spaces and strategic niche management for transitioning to circular economy. Int J Technol Manag Sustain Dev 2017;16(1). https://doi.org/10.1386/tmsd.16.1.25_1.
[3] Carayannis EG, Barth TD, Campbell DFJ. The Quintuple Helix innovation model: global warming as a challenge and driver for innovation. J Innov Entrep 2012;1:2. https://doi.org/10.1186/2192-5372-1-2.
[4] 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/10.1016/j.eist.2019.01.004.
[5] 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/10.1016/j.techfore.2016.06.008.
[6] Markard J, Truffer B. Technological innovation systems and the multi-level perspective: towards an integrated framework. Res Pol 2008;37:596–615. https://doi.org/10.1016/j.respol.2008.01.004.
[7] Geels FW. Regime resistance against low-carbon transitions: introducing politics and power into the multi-level perspective. Theor Cult Soc 2014;31(5). https://doi.org/10.1177/0263276414531627.
[8] Breiner S, Subrahmanian E, Sriram RD. Modeling the Internet of things: a foundational approach. Proc. Seventh Int. Work. Web Things, ACM 2016: 38–41.
[9] 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/10.1016/j.rser.2018.04.013.
[10] 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/10.1016/j.rser.2018.03.089.
[11] 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/10.1016/j.rser.2015.12.193.
[12] 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/10.1016/j.rser.2017.07.018.
[13] Sioshansi FP. Consumer, prosumer, prosumager: how service innovations will disrupt the utility business model. Academic Press; 2019.
[14] Gui EM, MacGill I. Typology of future clean energy communities: an exploratory structure, opportunities, and challenges. Energy Res Soc Sci 2018;35. https://doi.org/10.1016/j.erss.2017.10.019.
[15] Geels FW, Kern F, Fuchs G, Hinderer N, Kungl G, Mylan J, et al. The enactment of socio-technical transition pathways: a reformulated typology and a comparative multi-level analysis of the German and UK low-carbon electricity transitions (1990–2014). Res Pol 2016;45:896–913. https://doi.org/10.1016/j.respol.2016.01.015.
[16] Lindberg MB, Markard J, Andersen AD. Policies, actors and sustainability transition pathways: a study of the EU's energy policy mix. Res Pol 2019;48: 103668. https://doi.org/10.1016/j.respol.2018.09.003.
[17] Wittmayer JM, Avelino F, van Steenbergen F, Loorbach D. Actor roles in transition: insights from sociological perspectives. Environ Innov Soc Transitions 2017;24. https://doi.org/10.1016/j.eist.2016.10.003.
[18] Gliedt T, Hoicka CE, Jackson N. Innovation intermediaries accelerating environmental sustainability transitions. J Clean Prod 2018;174. https://doi.org/10.1016/j.jclepro.2017.11.054.
[19] 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/10.1016/j.scs.2017.06.018.
[20] 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.
[21] Gallagher CV, 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/10.1016/j.enbuild.2018.02.023.
[22] 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/10.1016/j.rser.2017.10.047.
[23] Pfenninger S, DeCarolis J, Hirth L, Quoilin S, Staffell I. The importance of open data and software: is energy research lagging behind? Energy Pol 2017;101: 211–5. https://doi.org/10.1016/j.enpol.2016.11.046.
[24] 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/10.1016/j.esr.2017.12.002.
[25] Openmod. Open energy modelling initiative (Openmod) - open models. https://wiki.openmod-initiative.org/wiki/Open_Models.
[26] Nastasi B, Manfren M, Noussan M. Open data and energy analytics. Energies 2020;13. https://doi.org/10.3390/en13092334.
[27] 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.
[28] Lund H, Arler F, Østergaard P, Hvelplund F, Connolly D, Mathiesen B, et al. Simulation versus optimisation: theoretical positions in energy system modelling. Energies 2017;10:840.
[29] DeCarolis J, Daly H, Dodds P, Keppo I, Li F, McDowall W, et al. Formalizing best practice for energy system optimization modelling. Appl Energy 2017;194:184–98. https://doi.org/10.1016/j.apenergy.2017.03.001.
[30] 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.
[31] Strachan N, Balta-Ozkan N, Joffe D, McGeevor K, Hughes N. Soft-linking energy systems and GIS models to investigate spatial hydrogen infrastructure development in a low-carbon UK energy system. Int J Hydrogen Energy 2009;34:642–57.
[32] Cui L, Kumara S, Albert R. Complex networks: an engineering view. IEEE Circ Syst Mag 2010;10:10–25. https://doi.org/10.1109/MCAS.2010.937883.
[33] Imam S, Coley DA, Walker I. The building performance gap: are modellers literate? Build Serv Eng Technol 2017;38:351–75. https://doi.org/10.1177/0143624416684641.
[34] de Wilde P. The building performance gap: are modellers literate? Build Serv Eng Technol 2017;38:757–9. https://doi.org/10.1177/0143624417728431.
[35] 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/10.1016/j.rser.2017.06.049.
[36] MacNaughton P, Cao X, Buonocore J, Cedeno-Laurent J, Spengler J, Bernstein A, et al. Energy savings, emission reductions, and health co-benefits of the green building movement. J Expo Sci Environ Epidemiol 2018;28:307.
[37] Scofield JH, Cornell J. A critical look at "Energy savings, emissions reductions, and health co-benefits of the green building movement. J Expo Sci Environ Epidemiol 2019;29:584–93. https://doi.org/10.1038/s41370-018-0078-1.
[38] 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/10.1016/j.rser.2018.06.060.
[39] Marquant JF, Evins R, Bollinger LA, Carmeliet J. A holarchic approach for multi-scale distributed energy system optimisation. Appl Energy 2017;208: 935–53. https://doi.org/10.1016/j.apenergy.2017.09.057.
[40] Reynolds J, Ahmad MW, Rezgui Y. Holistic modelling techniques for the operational optimisation of multi-vector energy systems. Energy Build n.d. 10.1016/j.enbuild.2018.03.065.
[41] 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/10.1016/j.egypro.2011.12.1104.
[42] Manfren M. Multi-commodity network flow models for dynamic energy management – mathematical formulation. Energy Procedia 2012;14: 1380–5. https://doi.org/10.1016/j.egypro.2011.12.1105.
[43] 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.
[44] Dorfner J. Open source modelling and optimisation of energy infrastructure at urban scale. Technische Universität München; 2016.
[45] Nastasi B, Lo Basso G. Hydrogen to link heat and electricity in the transition towards future Smart Energy Systems. Energy 2016;110:5–22. https://doi.org/10.1016/j.energy.2016.03.097.
[46] Antenucci A, Sansavini G. Extensive CO2 recycling in power systems via Power-to-Gas and network storage. Renew Sustain Energy Rev 2019;100: 33–43.
[47] 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/10.1016/j.apenergy.2012.10.031.

[48] Østergård T, Jensen RL, Maagaard SE. A comparison of six metamodeling techniques applied to building performance simulations. Appl Energy 2018;211:89–103. https://doi.org/10.1016/j.apenergy.2017.10.102.
[49] Abualdenien J, Borrmann A. A meta-model approach for formal specification and consistent management of multi-LOD building models. Adv Eng Inf 2019;40:135–53.
[50] Nutkiewicz A, Yang Z, Jain RK. Data-driven Urban Energy Simulation (DUE-S): a framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow. Appl Energy 2018;225:1176–89.
[51] Kuster C, Hippolyte J-L, Rezgui Y, Mourshed M. A simplified geo-cluster definition for energy system planning in Europe. Energy Procedia 2019;158:3222–7.
[52] Arregi B, Garay R. Regression analysis of the energy consumption of tertiary buildings. Energy Procedia 2017;122:9–14. https://doi.org/10.1016/j.egypro.2017.07.290.
[53] 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/10.1016/j.enbuild.2017.09.034.
[54] Tronchin L, Manfren M, Nastasi B. Energy analytics for supporting built environment decarbonisation. Energy Procedia 2019;157:1486–93. https://doi.org/10.1016/j.egypro.2018.11.313.
[55] ISO, ISO. 2018 Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) — information management using building information modelling — Part 1: concepts and principles. 2018. 19650-1.
[56] ISO. Energy performance of buildings — overarching EPB assessment — Part 1: general framework and procedures. 2017. 52000-1:2017.
[57] Preidel C, Borrmann A, Mattern H, König M, Schapke S-E. Common data environment. In: Borrmann A, König M, Koch C, Beetz J, editors. Build. Inf. Model. Technol. Found. Ind. Pract. Cham: Springer International Publishing; 2018. p. 279–91. https://doi.org/10.1007/978-3-319-92862-3_15.
[58] Radl J, Kaiser J. Benefits of implementation of common data environment (CDE) into construction projects. IOP Conf Ser Mater Sci Eng 2019;471:22021.
[59] Werbrouck J, Pauwels P, Beetz J, van Berlo L. Towards a decentralised common data environment using linked building data and the solid ecosystem. 36th CIB W78 2019 Conf.; 2019. p. 113–23.
[60] Agugiaro G, Benner J, Cipriano P, Nouvel R. The Energy Application Domain Extension for CityGML: enhancing interoperability for urban energy simulations. Open Geospatial Data, Softw Stand 2018;3:2. https://doi.org/10.1186/s40965-018-0042-y.
[61] Agugiaro G. 6 - open data-modeling standards for city-wide energy simulations. In: Eicker UBT-UES for L-CC. Academic Press; 2019. p. 241–55. https://doi.org/10.1016/B978-0-12-811553-4.00006-8.
[62] Soundararajan K, Ho HK, Su B. Sankey diagram framework for energy and exergy flows. Appl Energy 2014;136:1035–42. https://doi.org/10.1016/j.apenergy.2014.08.070.
[63] Abdelalim A, O'Brien W, Shi Z. Data visualization and analysis of energy flow on a multi-zone building scale. Autom ConStruct 2017;84:258–73. https://doi.org/10.1016/j.autcon.2017.09.012.
[64] Miller C, Nagy Z, Schlueter A. Automated daily pattern filtering of measured building performance data. Autom ConStruct 2015;49:1–17. https://doi.org/10.1016/j.autcon.2014.09.004.
[65] Bauwens G, Roels S. Co-heating test: a state-of-the-art. Energy Build 2014;82:163–72. https://doi.org/10.1016/j.enbuild.2014.04.039.
[66] 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/10.1016/j.enbuild.2016.03.030.
[67] 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 2018;18:2360. https://doi.org/10.3390/s18072360.
[68] 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/10.1016/j.enbuild.2019.03.006.
[69] 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/10.1016/j.enbuild.2014.03.070.
[70] Lin G, Claridge DE. A temperature-based approach to detect abnormal building energy consumption. Energy Build 2015;93:110–8. https://doi.org/10.1016/j.enbuild.2015.02.013.
[71] 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/10.1016/j.enbuild.2014.11.033.
[72] 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/10.1016/j.scs.2019.101900.
[73] Qomi MJA, Noshadravan A, Sobstyl JM, Toole J, Ferreira J, Pellenq RJ-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.
[74] Pasichnyi O, Wallin J, Kordas O. Data-driven building archetypes for urban building energy modelling. Energy 2019;181:360–77. https://doi.org/10.1016/j.energy.2019.04.197.
[75] 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.
[76] Lammers N, Kissock K, Abels B, Sever F. Measuring progress with normalized energy intensity. SAE Int J Mater Manuf 2011;4:460–7.
[77] Hallinan KP, Brodrick P, Northridge J, Kissock JK, Brecha RJ. Establishing building recommissioning priorities and potential energy savings from utility energy data. 2011.
[78] Server F, Kissock JK, Brown D, Mulqueen S. Estimating industrial building energy savings using inverse simulation. 2011.
[79] Abels B, Sever F, Kissock K, Ayele D. Understanding industrial energy use through lean energy analysis. SAE Int J Mater Manuf 2011;4:495–504.
[80] Masuda H, Claridge DE. Inclusion of building envelope thermal lag effects in linear regression models of daily basis building energy use data. 2012.
[81] 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/10.1016/j.enbuild.2012.10.050.
[82] Hitchin R, Knight I. Daily energy consumption signatures and control charts for air-conditioned buildings. Energy Build 2016;112:101–9. https://doi.org/10.1016/j.enbuild.2015.11.059.
[83] Paulus MT. Algorithm for explicit solution to the three parameter linear change-point regression model. Sci Technol Built Environ 2017;23:1026–35.
[84] 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. Build Eng 2015;121:156.
[85] 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.
[86] 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.
[87] 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.
[88] 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.
[89] 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.
[90] 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.
[91] Lindelöf D, Afshari H, Alisafaee M, Biswas J, Caban M, Mocellin X, et al. Field tests of an adaptive, model-predictive heating controller for residential buildings. Energy Build 2015;99:292–302. https://doi.org/10.1016/j.enbuild.2015.04.029.
[92] Gustin M, McLeod RS, Lomas KJ. Forecasting indoor temperatures during heatwaves using time series models. Build Environ 2018;143:727–39. https://doi.org/10.1016/j.buildenv.2018.07.045.
[93] Gustin M, McLeod RS, Lomas KJ. Can semi-parametric additive models outperform linear models, when forecasting indoor temperatures in free-running buildings? Energy Build 2019;193:250–66. https://doi.org/10.1016/j.enbuild.2019.03.048.
[94] 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/10.1016/j.energy.2018.09.037.
[95] 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.
[96] Allard I, Olofsson T, Nair G. Energy evaluation of residential buildings: performance gap analysis incorporating uncertainties in the evaluation methods. Build. Simul. 2018;11:725–37.
[97] Kavgic M, Mavrogianni A, Mumovic D, Summerfield A, Stevanovic Z, Djurovic-Petrovic M. A review of bottom-up building stock models for energy consumption in the residential sector. Build Environ 2010;45:1683–97. https://doi.org/10.1016/j.buildenv.2010.01.021.
[98] Foucquier A, Robert S, Suard F, Stéphan L, Jay A. State of the art in building modelling and energy performances prediction: a review. Renew Sustain Energy Rev 2013;23:272–88. https://doi.org/10.1016/j.rser.2013.03.004.
[99] Fumo N. A review on the basics of building energy estimation. Renew Sustain Energy Rev 2014;31:53–60. https://doi.org/10.1016/j.rser.2013.11.040.
[100] 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/10.1016/j.enbuild.2017.07.038.
[101] de Wilde P. The gap between predicted and measured energy performance of buildings: a framework for investigation. Autom ConStruct 2014;41:40–9. https://doi.org/10.1016/j.autcon.2014.02.009.
[102] Corgnati SP, Fabrizio E, Filippi M, Monetti V. Reference buildings for cost optimal analysis: method of definition and application. Appl Energy 2013;102:983–93. https://doi.org/10.1016/j.apenergy.2012.06.001.
[103] Kneifel J, Webb D. Predicting energy performance of a net-zero energy building: a statistical approach. Appl Energy 2016;178:468–83. https://doi.org/10.1016/j.apenergy.2016.06.013.
[104] Zangheri P, Armani R, Pietrobon M, Pagliano L. Identification of cost-optimal and NZEB refurbishment levels for representative climates and building typologies across Europe. Energy Effic 2018;11:337–69. https://doi.org/10.1007/s12053-017-9566-8.
[105] Goel S, Baker C, Wolf D, Henderson P, Wang N, Rosenberg M. A simplified energy modeling approach for buildings (C009). In: Build. Perform. Anal. Conf. SimBuild; 2018.
[106] Deru M, Field K, Studer D, Benne K, Griffith B, Torcellini P, et al. US Department of Energy commercial reference building models of the national building stock. 2011.
[107] Thornton BA, Rosenberg MI, Richman EE, Wang W, Xie Y, Zhang J, et al. Achieving the 30% goal: energy and cost savings analysis of ASHRAE Standard 90. 2011. p. 1–2010.
[108] Goel S, Athalye RA, Wang W, others. Enhancements to ASHRAE standard 90.1 prototype building models. 2014.
[109] 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.
[110] Zhao F, Lee SH, Augenbroe G. Reconstructing building stock to replicate energy consumption data. Energy Build 2016;117:301–12. https://doi.org/10.1016/j.enbuild.2015.10.001.
[111] 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.
[112] 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/10.1016/j.enbuild.2019.01.046.
[113] 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/10.1016/j.enbuild.2019.109337.
[114] 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.
[115] Naveros I, Ghiaus C, Ordoñez J, Ruiz DP. Thermal networks considering graph theory and thermodynamics. In: 12th Int. Conf. Heat Transf. Fluid Mech. Thermodyn.; 2016.
[116] Naveros I, Ghiaus C, Ordoñez J, Ru\'\iz DP. Thermal networks from the heat equation by using the finite element method. WIT Trans Eng Sci 2016;106:33–43.
[117] Raillon L, Ghiaus C. Study of error propagation in the transformations of dynamic thermal models of buildings. J Contr Sci Eng 2017;2017.
[118] 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/10.1016/j.enbuild.2016.03.054.
[119] 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/10.1016/j.enbuild.2012.12.007.
[120] 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.
[121] Masuda H, Claridge D. Estimation of building parameters using simplified energy balance model and metered whole building energy use. 2012.
[122] 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/10.1016/j.scs.2015.11.003.
[123] 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.
[124] Jentsch MF, Bahaj AS, James PAB. Climate change future proofing of buildings—generation and assessment of building simulation weather files. Energy Build 2008;40:2148–68. https://doi.org/10.1016/j.enbuild.2008.06.005.
[125] 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/10.1016/j.renene.2012.12.049.
[126] 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/10.1016/j.enbuild.2019.109556.
[127] 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.
[128] 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;84. https://doi.org/10.1016/j.enbuild.2014.08.012.
[129] 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/10.1016/j.apenergy.2015.04.114.
[130] 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.
[131] 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/10.1016/j.applthermaleng.2013.03.053.
[132] Tronchin L, Fabbri K. Analysis of buildings' energy consumption by means of exergy method. Int J Exergy 2008;5:605–25.
[133] Meggers F, Ritter V, Goffin P, Baetschmann M, Leibundgut H. Low exergy building systems implementation. Energy 2012;41:48–55. https://doi.org/10.1016/j.energy.2011.07.031.
[134] 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/10.1016/j.rser.2018.05.002.
[135] 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.
[136] Jayaweera T, Haeri H, Gowans D. The Uniform methods project: methods for determining energy efficiency savings for specific measures. Contract 2013;303:275–3000.
[137] 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/10.1016/j.enbuild.2016.03.059.
[138] Gunay B, Shen W, Yang C. Characterization of a building's operation using automation data: a review and case study. Build Environ 2017;118:196–210. https://doi.org/10.1016/j.buildenv.2017.03.035.
[139] 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/10.1016/j.rser.2017.10.006.
[140] Vogt LJ. Electricity pricing: engineering principles and methodologies. CRC Press; 2017.
[141] Price P. Methods for analyzing electric load shape and its variability. 2010.
[142] Kurnik CW, Stern F, Spencer J. Peak demand and time-differentiated energy savings cross-cutting protocol. The Uniform methods project: methods for determining energy efficiency savings for specific measures. 2017.
[143] Jenkins DP, Patidar S, Simpson SA. Synthesising electrical demand profiles for UK dwellings. Energy Build 2014;76:605–14. https://doi.org/10.1016/j.enbuild.2014.03.012.
[144] Ramírez-Mendiola JL, Grünewald P, Eyre N. The diversity of residential electricity demand – a comparative analysis of metered and simulated data. Energy Build 2017;151:121–31. https://doi.org/10.1016/j.enbuild.2017.06.006.
[145] Pflugradt N, Platzer B. Behavior based load profile generator for domestic hot water and electricity use. In: 12th int. Conf. Energy storage (innostock), Lleida, Spain; 2012.
[146] Pflugradt N, Teuscher J, Platzer B, Schufft W. Analysing low-voltage grids using a behaviour based load profile generator. Int. Conf. Renew. Energies Power Qual. 2013;11:5.
[147] Poncelet K, Delarue E, Six D, Duerinck J, D'haeseleer W. Impact of the level of temporal and operational detail in energy-system planning models. Appl Energy 2016;162:631–43. https://doi.org/10.1016/j.apenergy.2015.10.100.
[148] Fischer D, Madani H. On heat pumps in smart grids: a review. Renew Sustain Energy Rev 2017;70:342–57. https://doi.org/10.1016/j.rser.2016.11.182.
[149] Love J, Smith AZP, Watson S, Oikonomou E, Summerfield A, Gleeson C, et al. The addition of heat pump electricity load profiles to GB electricity demand: evidence from a heat pump field trial. Appl Energy 2017;204:332–42. https://doi.org/10.1016/j.apenergy.2017.07.026.
[150] Qadrdan M, Fazeli R, Jenkins N, Strbac G, Sansom R. Gas and electricity supply implications of decarbonising heat sector in GB. Energy 2019;169:50–60. https://doi.org/10.1016/j.energy.2018.11.066.
[151] Singh Gaur A, Fitiwi DZ, Curtis J. Heat pumps and their role in decarbonising heating sector: a comprehensive review. ESRI WP627; June 2019 2019.
[152] Narula K, Chambers J, Streicher KN, Patel MK. Strategies for decarbonising the Swiss heating system. Energy 2019;169:1119–31. https://doi.org/10.1016/j.energy.2018.12.082.
[153] Quiggin D, Buswell R. The implications of heat electrification on national electrical supply-demand balance under published 2050 energy scenarios. Energy 2016;98:253–70. https://doi.org/10.1016/j.energy.2015.11.060.
[154] Bloess A, Schill W-P, Zerrahn A. Power-to-heat for renewable energy integration: a review of technologies, modeling approaches, and flexibility potentials. Appl Energy 2018;212:1611–26. https://doi.org/10.1016/

j.apenergy.2017.12.073.
[155] Gaur AS, Fitiwi DZ, Curis J. Implications of power-to-heat on transmission expansion needs: a real life case study. IEEE Milan PowerTech; 2019. p. 1–6. https://doi.org/10.1109/PTC.2019.8810477.
[156] 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/10.1016/j.apenergy.2018.05.037.
[157] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807. https://doi.org/10.1016/j.rser.2015.01.057.
[158] Kohlhepp P, Harb H, Wolisz H, Waczowicz S, Müller D, Hagenmeyer V. Large-scale grid integration of residential thermal energy storages as demand-side flexibility resource: a review of international field studies. Renew Sustain Energy Rev 2019;101:527–47. https://doi.org/10.1016/j.rser.2018.09.045.
[159] Vijay A, Hawkes A. Demand side flexibility from residential heating to absorb surplus renewables in low carbon futures. Renew Energy 2019;138: 598–609. https://doi.org/10.1016/j.renene.2019.01.112.
[160] Eggimann S, Hall JW, Eyre N. A high-resolution spatio-temporal energy demand simulation to explore the potential of heating demand side management with large-scale heat pump diffusion. Appl Energy 2019;236: 997–1010. https://doi.org/10.1016/j.apenergy.2018.12.052.
[161] Müller FL, Jansen B. Large-scale demonstration of precise demand response provided by residential heat pumps. Appl Energy 2019;239:836–45. https://doi.org/10.1016/j.apenergy.2019.01.202.
[162] Facci AL, Krastev VK, Falcucci G, Ubertini S. Smart integration of photovoltaic production, heat pump and thermal energy storage in residential applications. Sol Energy 2019;192:133–43. https://doi.org/10.1016/j.solener.2018.06.017.
[163] Oliveira-Lima JA, Delgado-Gomes V, Martins JF, Lima C. Standard-based service-oriented infrastructure to integrate intelligent buildings in distributed generation and smart grids. Energy Build 2014;76. https://doi.org/10.1016/j.enbuild.2014.03.013.
[164] Sun M, Djapic P, Aunedi M, Pudjianto D, Strbac G. Benefits of smart control of hybrid heat pumps: an analysis of field trial data. Appl Energy 2019;247: 525–36. https://doi.org/10.1016/j.apenergy.2019.04.068.
[165] Gui EM, MacGill I. Consumer-centric service innovations in an era of self-selecting customers. Consum Prosumer, Prosumager How Serv Innov Will Disrupt Util Bus Model 2019:127.
[166] Clauß J, Finck C, Vogler-Finck P, Beagon P. Control strategies for building energy systems to unlock demand side flexibility–A review. In: IBPSA Build. Simul.; 2017. San Fr. 7-9 August 2017.
[167] Péan TQ, Salom J, Costa-Castelló R. Review of control strategies for improving the energy flexibility provided by heat pump systems in buildings. J Process Contr 2019;74:35–49. https://doi.org/10.1016/j.jprocont.2018.03.006.
[168] Clauß J, Georges L. Model complexity of heat pump systems to investigate the building energy flexibility and guidelines for model implementation. Appl Energy 2019;255:113847. https://doi.org/10.1016/j.apenergy.2019.113847.
[169] Bellocchi S, Manno M, Noussan M, Prina MG, Vellini M. Electrification of transport and residential heating sectors in support of renewable penetration: scenarios for the Italian energy system. Energy 2020;196:117062. https://doi.org/10.1016/j.energy.2020.117062.
[170] Ulbig A, Coccolo S, Kämpf J. Assessing the challenges of changing electricity demand profiles caused by evolving building stock and climatic conditions on distribution grids. Proc. Int. Conf. CISBAT 2015 Futur. Build. Dist. Sustain. from Nano to Urban Scale 2015:791–6.
[171] Barton J, Huang S, Infield D, Leach M, Ogunkunle D, Torriti J, et al. The evolution of electricity demand and the role for demand side participation, in buildings and transport. Energy Pol 2013;52:85–102. https://doi.org/10.1016/j.enpol.2012.08.040.
[172] Hayn M, Bertsch V, Fichtner W. Electricity load profiles in Europe: the importance of household segmentation. Energy Res Soc Sci 2014;3:30–45. https://doi.org/10.1016/j.erss.2014.07.002.
[173] Pasaoglu G, Fiorello D, Zani L, Martino A, Zubaryeva A, Thiel C. Projections for electric vehicle load profiles in Europe based on travel survey data. Netherlands: Jt Res Cent Eur Comm Petten; 2013.
[174] Schäuble J, Kaschub T, Ensslen A, Jochem P, Fichtner W. Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany. J Clean Prod 2017;150:253–66. https://doi.org/10.1016/j.jclepro.2017.02.150.
[175] Xu Y, Çolak S, Kara EC, Moura SJ, González MC. Planning for electric vehicle needs by coupling charging profiles with urban mobility. Nat Energy 2018;3: 484–93. https://doi.org/10.1038/s41560-018-0136-x.
[176] Soares J, Borges N, Fotouhi Ghazvini MA, Vale Z, de Moura Oliveira PB. Scenario generation for electric vehicles' uncertain behavior in a smart city environment. Energy 2016;111:664–75. https://doi.org/10.1016/j.energy.2016.06.011.
[177] Khanna N, Fridley D, Zhou N, Karali N, Zhang J, Feng W. Energy and CO2 implications of decarbonization strategies for China beyond efficiency: modeling 2050 maximum renewable resources and accelerated electrification impacts. Appl Energy 2019;242:12–26. https://doi.org/10.1016/j.apenergy.2019.03.116.
[178] 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/10.1016/j.apenergy.2015.08.089.
[179] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. Energy 2014;65:1–17. https://doi.org/10.1016/j.energy.2013.10.041.
[180] Stadler M, Groissböck M, Cardoso G, Marnay C. Optimizing distributed energy resources and building retrofits with the strategic DER-CAModel. Appl Energy 2014;132:557–67. https://doi.org/10.1016/j.apenergy.2014.07.041.
[181] Steen D, Stadler M, Cardoso G, Groissböck M, DeForest N, Marnay C. Modeling of thermal storage systems in MILP distributed energy resource models. Appl Energy 2015;137:782–92. https://doi.org/10.1016/j.apenergy.2014.07.036.
[182] Mashayekh S, Stadler M, Cardoso G, Heleno M. A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids. Appl Energy 2017;187:154–68. https://doi.org/10.1016/j.apenergy.2016.11.020.
[183] Evins R, Orehounig K, Dorer V, Carmeliet J. New formulations of the 'energy hub' model to address operational constraints. Energy 2014;73:387–98. https://doi.org/10.1016/j.energy.2014.06.029.
[184] Morvaj B, Evins R, Carmeliet J. Optimization framework for distributed energy systems with integrated electrical grid constraints. Appl Energy 2016;171:296–313. https://doi.org/10.1016/j.apenergy.2016.03.090.
[185] Morvaj B, Evins R, Carmeliet J. Optimising urban energy systems: simultaneous system sizing, operation and district heating network layout. Energy 2016;116:619–36. https://doi.org/10.1016/j.energy.2016.09.139.
[186] 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/10.1016/j.enbuild.2018.12.003.
[187] Griego D, Schopfer S, Henze G, Fleisch E, Tiefenbeck V. Aggregation effects for microgrid communities at varying sizes and prosumer-consumer ratios. Energy Procedia 2019;159:346–51. https://doi.org/10.1016/j.egypro.2019.01.004.
[188] Huang P, Lovati M, Zhang X, Bales C, Hallbeck S, Becker A, et al. Transforming a residential building cluster into electricity prosumers in Sweden: optimal design of a coupled PV-heat pump-thermal storage-electric vehicle system. Appl Energy 2019;255:113864. https://doi.org/10.1016/j.apenergy.2019.113864.
[189] Rodriguez LG, Martini I, Discoli C. Energy storage for residential dwellings. Methodology to improve energy efficiency and habitability. J Energy Storage 2016;8:99–110. https://doi.org/10.1016/j.est.2016.09.009.
[190] Baranzelli C, Lavalle C, Sgobbi A, Aurambout J, Trombetti M, Jacobs-Crisioni C, Cristobal J, Kancs DKB. JRC Technical reports - regional Energy. Regional patterns of energy production and consumption factors in Europe. 2016.
[191] UK. Department of Business. Energy and Industrial strategy. A future framework for heat in buildings - call for evidence - government response. 2018.
[192] European Commission. European Commission - energy use in buildings. https://ec.europa.eu/energy/eu-buildings-factsheets-topics-tree/energy-use-buildings_en.
[193] Herrando M, Pantaleo AM, Wang K, Markides CN. Solar combined cooling, heating and power systems based on hybrid PVT, PV or solar-thermal collectors for building applications. Renew Energy 2019;143:637–47. https://doi.org/10.1016/j.renene.2019.05.004.
[194] Hawlader MNA, Chou SK, Ullah MZ. The performance of a solar assisted heat pump water heating system. Appl Therm Eng 2001;21:1049–65. https://doi.org/10.1016/S1359-4311(00)00105-8.
[195] Andersen AN, Østergaard PA. Support schemes adapting district energy combined heat and power for the role as a flexibility provider in renewable energy systems. Energy 2020;192:116639. https://doi.org/10.1016/j.energy.2019.116639.
[196] Luthander R, Widén J, Nilsson D, Palm J. Photovoltaic self-consumption in buildings: a review. Appl Energy 2015;142:80–94. https://doi.org/10.1016/j.apenergy.2014.12.028.
[197] Li Y, Wang C, Li G, Wang J, Zhao D, Chen C. Improving operational flexibility of integrated energy system with uncertain renewable generations considering thermal inertia of buildings. Energy Convers Manag 2020;207:112526. https://doi.org/10.1016/j.enconman.2020.112526.
[198] Zheng J, Zhou Z, Zhao J, Wang J. Integrated heat and power dispatch truly utilizing thermal inertia of district heating network for wind power integration. Appl Energy 2018;211:865–74. https://doi.org/10.1016/j.apenergy.2017.11.080.
[199] Li X, Li W, Zhang R, Jiang T, Chen H, Li G. Collaborative scheduling and flexibility assessment of integrated electricity and district heating systems utilizing thermal inertia of district heating network and aggregated buildings. Appl Energy 2020;258:114021. https://doi.org/10.1016/j.apenergy.2019.114021.
[200] Wang H, Meng H. Improved thermal transient modeling with new 3-order numerical solution for a district heating network with consideration of the pipe wall's thermal inertia. Energy 2018;160:171–83. https://doi.org/10.1016/j.energy.2018.06.214.
[201] Yoon JH, Bladick R, Novoselac A. Demand response for residential buildings based on dynamic price of electricity. Energy Build 2014;80:531–41. https://doi.org/10.1016/j.enbuild.2014.05.002.
[202] Yalcintas M, Hagen WT, Kaya A. An analysis of load reduction and load

shifting techniques in commercial and industrial buildings under dynamic electricity pricing schedules. Energy Build 2015;88:15–24. https://doi.org/10.1016/j.enbuild.2014.11.069.

[203] Hall S, Roelich K. Business model innovation in electricity supply markets: the role of complex value in the United Kingdom. Energy Pol 2016;92: 286–98. https://doi.org/10.1016/j.enpol.2016.02.019.

[204] Sahari A. Electricity prices and consumers' long-term technology choices: evidence from heating investments. Eur Econ Rev 2019;114:19–53. https://doi.org/10.1016/j.euroecorev.2019.02.002.

[205] Alberini A, Gans W, Velez-Lopez D. Residential consumption of gas and electricity in the U.S.: the role of prices and income. Energy Econ 2011;33: 870–81. https://doi.org/10.1016/j.eneco.2011.01.015.

[206] Vincent R, Ait-Ahmed M, Houari A, Benkhoris MF. Residential microgrid energy management considering flexibility services opportunities and forecast uncertainties. Int J Electr Power Energy Syst 2020;120:105981. https://doi.org/10.1016/j.ijepes.2020.105981.

[207] Ahmad T, Zhang H, Yan B. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustain Cities Soc 2020;55:102052. https://doi.org/10.1016/j.scs.2020.102052.

[208] Neirotti F, Noussan M, Simonetti M. Towards the electrification of buildings heating - real heat pumps electricity mixes based on high resolution operational profiles. Energy 2020;195:116974. https://doi.org/10.1016/j.energy.2020.116974.

[209] Pan W. System boundaries of zero carbon buildings. Renew Sustain Energy Rev 2014;37:424–34. https://doi.org/10.1016/j.rser.2014.05.015.

[210] Wang N, Phelan PE, Gonzalez J, Harris C, Henze GP, Hutchinson R, et al. Ten questions concerning future buildings beyond zero energy and carbon neutrality. Build Environ 2017;119:169–82. https://doi.org/10.1016/j.buildenv.2017.04.006.

[211] Vialetto G, Noro M, Rokni M. Combined micro-cogeneration and electric vehicle system for household application: an energy and economic analysis in a Northern European climate. Int J Hydrogen Energy 2017;42:10285–97. https://doi.org/10.1016/j.ijhydene.2017.01.035.

[212] Basir Khan MR, Jidin R, Pasupuleti J. Multi-agent based distributed control architecture for microgrid energy management and optimization. Energy Convers Manag 2016;112:288–307. https://doi.org/10.1016/j.enconman.2016.01.011.

[213] Kyriakarakos G, Dounis AI, Rozakis S, Arvanitis KG, Papadakis G. Polygeneration microgrids: a viable solution in remote areas for supplying power, potable water and hydrogen as transportation fuel. Appl Energy 2011;88:4517–26. https://doi.org/10.1016/j.apenergy.2011.05.038.

[214] Alanne K, Cao S. Zero-energy hydrogen economy (ZEH2E) for buildings and communities including personal mobility. Renew Sustain Energy Rev 2017;71:697–711. https://doi.org/10.1016/j.rser.2016.12.098.

[215] IRENA Report. Battery storage for renewables: market status and technology outlook 2015. Available at: https://www.irena.org/documentdownloads/publications/irena_battery_storage_report_2015.pdf, . [Accessed 13 June 2018] [n.d], report.

[216] Olaszi BD, Ladanyi J. Comparison of different discharge strategies of grid-connected residential PV systems with energy storage in perspective of optimal battery energy storage system sizing. Renew Sustain Energy Rev 2017;75:710–8. https://doi.org/10.1016/j.rser.2016.11.046.

[217] Gioutsos DM, Blok K, van Velzen L, Moorman S. Cost-optimal electricity systems with increasing renewable energy penetration for islands across the globe. Appl Energy 2018;226:437–49. https://doi.org/10.1016/j.apenergy.2018.05.108.