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**DOI**
10.1016/j.rser.2018.06.060

**Publication date**
2018

**Document Version**
Final published version

**Published in**
Renewable & Sustainable Energy Reviews

Renewable and Sustainable Energy Reviews 95 (2018) 341–353

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

# Energy efficiency, demand side management and energy storage technologies – A critical analysis of possible paths of integration in the built environment

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ARTICLE INFO

*Keywords:*
Energy transition modelling in the built environment
Multi-level perspective planning
Technologies for sustainable buildings
Demand side management
Energy storage systems
Power to heat
Power to gas

ABSTRACT

The transition towards energy systems characterized by high share of weather dependent renewable energy sources poses the problem of balancing the mismatch between inflexible production and inelastic demand with appropriate solutions, which should be feasible from the techno-economic as well as from the environmental point of view. Temporal and spatial decoupling of supply and demand is an important element to be considered for the evolution of built environment, especially when creating sectorial level planning strategies and policies. Energy efficiency measures, on-site generation technologies, demand side management and storage systems are reshaping energy infrastructures and energy market, together with innovative business models. Optimal design and operational choices in buildings are systemic, but buildings are also nodes in infrastructural systems and model-based approaches are generally used to guide decision-making processes, at multiple scale. Built environment could represent a suitable intermediate scale of analysis in Multi-Level Perspective planning, collocated among infrastructures and users. Therefore, the spatial and temporal scalability of modelling techniques is analysed, together with the possibility of accommodating multiple stakeholders' perspectives in decision-making, thereby finding synergies across multiple sectors of energy demand. For this reason, the paper investigates first the cross-sectorial role of models in the energy sector, because the use of common principles and techniques could stimulate a rapid development of multi-disciplinary research, aimed at sustainable energy transitions. Further, relevant issues for the integration of energy storage in built environment are described, considering their relationship with energy efficiency measures, on-site generation and demand side management.

## 1. Introduction

The transition towards energy systems characterized by high share of renewable energy sources (RES) is necessary to reduce drastically carbon emission and avoid climate change related risks. Buildings have a great impact in terms of carbon emission at the EU [1], US and global scale [2] and the issue of resource efficiency for the building sector [3] is becoming increasingly relevant, highlighting the need for a systemic view and adequate policies, as well as adjustments in the energy market [4]. At EU level, for example, building accounts for approximately 40% of carbon emission, determined by their direct energy use [1,5], and for about half of the extracted materials, half of energy consumption, one third of water consumption, and one third of waste generated, if we consider the direct and indirect impact of the whole sector [6]. Additionally, at the global level, the rapid urbanization trend determines the need for a concentration of research and development efforts in the built environment area. From a practical stand-point, we have to prioritize actions, i.e. define policies able to cope effectively with the underlying problems, considering realistically technical, economic, social and environmental constraints.

Energy efficiency measures and, in particular, deep retrofit strategies for the existing building stock can constitute a great opportunity [7,8], considering also the convergence of economic [9] and technological paradigms, focusing on intelligent assets [10], and the emergence of innovative business models [11], which can contribute to reshape the energy market and to create new economic development. The transition from the present energy paradigm to a sustainable one is a great challenge that requires an open multi-disciplinary approach

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https://doi.org/10.1016/j.rser.2018.06.060
Received 25 April 2018; Received in revised form 22 June 2018; Accepted 25 June 2018
Available online 01 July 2018

[12,13], based on the quadruple helix model of innovation [14,15], in which civil society organisations, industry, government and academia collaborate to share knowledge and data. In this sense, data models are essential to address analytically the problem of transitions [16–18] and a particular attention should be devoted to the role of open data and software [17] and optimization [18] formulations. Design, construction and operation practices in the building sector can profoundly benefit from the ongoing development in this area, using ontologies, semantic web technologies [19] and appropriate data formats [20]. High efficiency buildings are technically and economically feasible today [21] and Nearly Zero Energy Building (NZEB) paradigm [22], both for new and existing buildings, combines a radical energy demand reduction with on-site or nearby renewable energy supply. However, a high penetration of weather dependent RES poses the problem of balancing the mismatch between inflexible production and inelastic demand [23,24] and of being able to integrate it properly in the built environment [25] as well. On the infrastructural side, these technical issues can determine a consistent limit for the effective deployment of policies in this direction, as different countries at the EU level could reach in a few years limits in terms of RES penetration, if no adjustments will be done [26]. On the built environment side, the use of conventional electric energy storage technologies and systems are analysed with the scope of selecting profitable design configurations for customers [27].

As a matter of fact, this technology to achieve a complete self-sufficiency in buildings may be practically infeasible from the techno-economic (but also environmental) point of view, even in the case of a radical reduction of the cost of technologies, due to the necessity of long-term storage (to balance the seasonality of demands) when heating and cooling are supplied by electricity. These factors should be acknowledged when passing from building-level impacts to system wide impact on infrastructures [28]. Power-to-What (P2X) technologies, such as Power to Heat [29–31], Power to Hydrogen and Power to Gas [32–34] are opening new possibilities by combining the temporal and spatial decoupling of supply and demand with an interplay among different sectors in the energy system and among multiple energy carriers. Further, the present state of the art of research in decentralized energy systems is embodied in concepts such as Multi Energy Systems [35] and Energy Hubs [36,37], which can guarantee scalability and flexibility of application, from buildings to districts/neighbourhoods and cities. A relevant research effort has been devoted, in the last years, to the development of optimization models for energy hubs and multi-energy system [38], including simplification of electrical grid constraints [39,40], and thermal storage behaviour [41].

However, there could be further improvements with respect to modelling of temperature levels [42], selection of multi-objective optimal solutions [43], evaluation of stakeholders' perspectives and constraints [44], prediction of systems' operation [45], among others. Additionally, the applicability of calibrated data-driven models for energy management has been tested in extensively [46,47], showing a potential continuity with research dealing with building performance gap [48,49], considering also the incoming problem of embodied energy [50] and of long-term performance monitoring and data analysis [51].

For these reasons, this article introduces first relevant concepts such as Multi-Level Perspective planning [52] and analysis of complementarities [53] in sustainability transitions, to clarify the research background. After that, the article investigates the cross-sectorial role of models in the energy sector, because the use of common principles and techniques could stimulate a rapid development of multi-disciplinary research, aimed at sustainable energy transitions. Finally, the importance of demand side management and storage technologies is acknowledged, presenting relevant issues for their integration in the built environment. The goal of the article is indicating relevant elements to be considered for the evolution of research in built environment, insisting in particular on the scalability of techno-economic optimization and inverse modelling techniques, which can be further integrated and improved with respect to the current state of the art, following a continuous improvement strategy, empirically grounded.

## 2. Energy transitions planning

The topic of transition planning towards a low carbon and sustainable society is gaining increasingly importance. In fact, the transition from the present environmental, economic and societal paradigm to a sustainable one is a great challenge that requires a multi-disciplinary approach to innovation in which civil society organisations, industry, government and academia work together, in a quadruple helix model [14,15], to share knowledge and data among each other. In this framework, open data and software represent an enabling technology [17]. Further, experts in modelling and technology foresight cover a cross-disciplinary role for strategic decision-making, which encompasses clearly the implementation of cleaner energy systems, but which impacts, more in general, how we live, work and move in a profound way, determining potentially a structural change for its adoption [54]. Built environment is considered today one of the most important sectors for the implementation of circular economy models [9], which can guarantee long-term development perspectives to investors and, at the same time, can create multiple shared advantages [55]. Circular economy models for the building sector are routed in the following main features [9]:

1. sharing of assets and flexibility in the use of spaces;
2. efficient use by delivering utility virtually (tele-working, virtualization of services and processes, etc.);
3. optimal design and operation of buildings;
4. use of renewable energy sources;
5. modularity, flexibility, re-manufacturing of building components;
6. substitution of technologies with more efficient ones (energy efficient renovation).

In all these features we can identify synergies with the deployment of policies oriented towards energy efficiency and renewable energy use. For this reason, it is possible to envision a path of convergence between short-term economic objectives (i.e. job creation, economic growth, etc.) and long-term environmental objectives (i.e. decarbonisation, resource efficiency and sustainability) for the building sector. In general, improving energy efficiency in multiple sectors of economy requires appropriate legislation, successful market strategies and collaboration between private and public sectors. The increase of energy efficiency investments with respect to present state is crucial for the transition towards more competitive, secure and sustainable energy systems. More specifically for the building sector, energy renovation has a relevant role today [7]. However, the progressive refurbishment and substitution of inefficient building stock requires long-term planning. Planning should incorporate existing policy frameworks for growth, employment, energy and climate in order to create an effective energy renewal market that would increase employment and reduce energy demand in the building sector.

### 2.1. Multi-level perspective planning

Analysing and modelling at multiple levels the dynamics previously described requires the evolution of present tools and methodologies, including more adequate description of techno-economic and socio-economic aspects [12,16]. The evolution process will be driven by different types of stakeholders, including prosumers [11], which can act as investors on the energy market and can participate to relevant decision-making processes. It is worth noticing that the techno-economic side of the problem cannot be considered separately from the socio-economic side with respect to policy questions regarding stakeholders' behaviour and social acceptability of technical solutions.

Today, technological innovation is more and more informationcentric [17] and energy technologies, as well, can benefit from digitization processes. The availability of large scale data could potentially enable the evaluation of the behavioural and social impact of technologies, giving, for example, information at multiple levels and fast feedback on the result of policies. These could, in turn, help overcoming progressively the limitations of current models of technological learning which are not effective in a fast evolving landscape. Often, models aimed at describing complex system derive from experts vision and judgement [56] while, the direct engagement of citizens as prosumers calls for policy-driven models and practices considering justice and community fairness framework [57]. From a practical standpoint, it is necessary to unveil, by means of data and models, the connections among multiple aspects of sustainability (environment, economy and society), multiple levels of analysis (e.g., technologies, infrastructures, policies) and to adopt performance indicators to monitor and analyze critically the evolution of systems. Indeed, key performance indicators (KPI) are essential to guide specific planning, design and operation choices. As such, sustainability transitions require multi-level perspective [58] and strategies to redirect the existing dynamics in economy, society and technology, considering realistically all the inherent constraints which are present in the path-dependent co-evolution of the social, technological, industrial and policy frameworks. An

example in this sense is the so-called social energy system approach [59], when energy systems literacy, project community literacy and political literacy are considered together. A term used in literature for this is Multi-Level Perspective (MLP) planning [12,52,60] and considers three fundamental levels:

1. energy infrastructures (i.e. energy systems and technologies);
2. behaviour (i.e. consumer's and investor's choices);
3. institutional factor (i.e. policy, regulation, and markets).

Most of the existing tools and methodologies in the energy sector are focused on the quantitative analysis of the development of energy infrastructures and systems, structured on different levels of analysis. There are today very good bottom-up energy system models (engineering applications and micro-economic perspective) and top-down macro-economic models to support decision-making [61,62]. However, tools and methods focused on the analysis of the behaviour of consumers and investors are moderately covered and deficiencies are present also in the analysis of institutional factors driving decision, especially on a local scale. In other words, there is an evident difficulty in consolidating top-down indications with bottom-up actions in energy systems. Additionally, considering the fact that today a relevant part of the evolution of energy systems depends on local and individual choices [11], the analysis of complementarities in energy transitions and building energy modelling research can help overcoming these issues, as will be described in more detail in the next sections.

### 2.2. Analysis of complementarities in energy transitions

In order to go more in depth with respect to technological and sectorial components of the problem of energy storage, we consider a framework for analysis of complementarities presented in literature [53]. In this framework technology is considered as the focal element and four blocks of concepts are used for its analysis: different relationships, different components, different purposes and complementary dynamics. First, different relationships are described by means of a unilateral/bi-lateral/absolute dependency, starting from the identification of the technology that receives the benefits. This dependency can have different degrees of intensity (e.g. from weak to strong) and can be critical or non-critical for technology success. After that, various components have to be considered for complementarities, namely technological (e.g. other technologies positively affect focal technology), organizational (e.g. business models across different levels of the value chain) institutional (e.g. technology support and regulatory programs), and infrastructure (e.g. generic element affecting positively technology). Further, different purposes can be considered, for example technological purposes when the focus is reducing price or increasing performance, sectorial when the focus is societal needs through the eyes of policy makers and regulatory authorities. Finally, all the previous three blocks (relationships, components, purpose) have to be analysed with respect to their evolution dynamics in time. In this work, considering energy storage systems as the focal technology, we can identify relationships first. The most relevant relationships are the ones with energy efficiency measures (on the demand side), on-site generation technologies (on the supply side) and demand side management. All these relationships are substantially bilateral as building systems should be conceived considering cost optimal levels of performance [63] and sizing and operation strategies have to be determined in an integrated way [64,65]. The relevant modelling issues involved are described in Section 3. Instead, in Section 4 a demand side management and energy storage literature is presented. What we would like to stress here is the possibility today of dealing with data related to energy transition processes with a much wider perspective on sustainability [66]. What appears to be evident is the possibility of visualizing synthetically (using appropriate tools) highly complex problems, represented by multivariate data structures [67,68], thereby, contributing to better decision-making processes, when different type of stakeholders are involved.

### 2.3. The role of data-driven approaches for built environment evolution

Building performance can be studied by means of Key Performance Indicators (KPIs) [66,69–71], generally aimed at aggregating a larger set of data in a single representative quantity. KPI can be used to describe both design and operational performance. First, if we consider simulation-based optimization [64,72] in design phase, surrogate models are considered among the most promising techniques to overcome the limitations given by the dimension of optimization problems. The choice of a specific technique can depend on several factors [73]. Further, the proper exploration of design space is crucial and, for this reason, Design of Experiments and parametric design have received an increasing attention in recent years [74,75], consider also Building Information Modelling (BIM) for data standardization [76–78].

Additionally, considering multiple hypotheses in design phase appears even more important if we consider the potential gap between simulated and measured performance [48,49,79].

Going back to surrogate models, we can find in recent literature several examples of multi-variate regression models to support design optimization [80–84], considering also topics such as cost-optimal analysis [63,85–87] and energy performance contracting [88,89]. Fig. 1 summarizes relevant steps in the design process:

1. collecting information, from general open data, to statistics and regulations;
2. processing of information, consider customer and market perspective, together with sustainability issues;
3. design (iterative search of solution);
4. evaluation with respect to selected KPIs;
5. impact in terms of performance and cost, considering life cycle.

Fig. 1 can be read horizontally following the different perspective of stakeholders and users. Indeed, first line mainly refers to users and owners and the second one characterized by black-contour boxes can be handled as the development of an economic issue from the initial statistics to its final cost inventory. Furthermore, the third line shows the main regulations, targets and lifespan perspective considering the new object to design, i.e. the building, as an added value to people and ecosystem. As already mentioned, the design process is iterative and has to exploit multiple feedbacks.

Finally, with respect to operation phase issues, relevant elements for

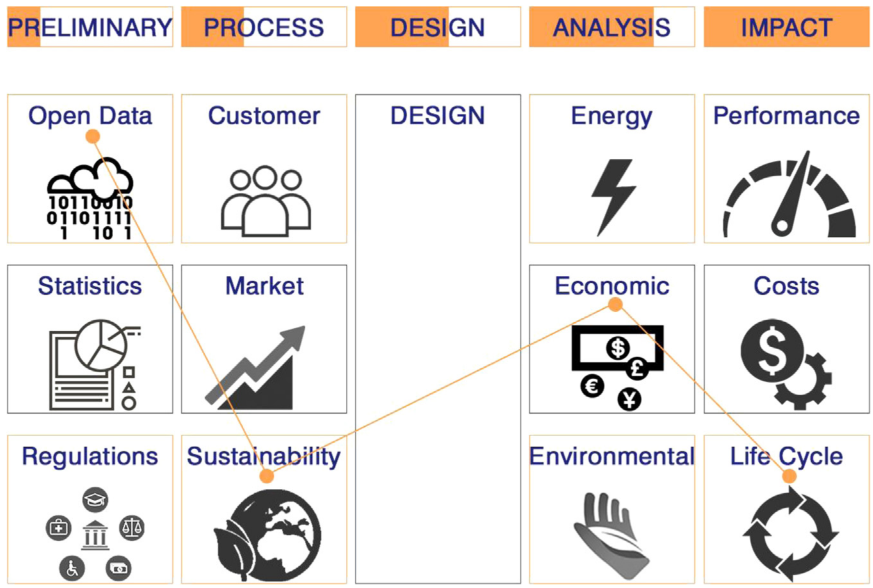


**Fig. 1.** Design process phases and interaction among fields.

the choice of surrogate modelling techniques are:

1. conceptual simplicity and ease of implementation [90], with temperature as the main regressor [91] and energy balance control [92];
2. automated or partially automated model selection [47,93], including testing methodology [94–96];
3. ability to account for the impact of different operational strategies and conditions [97–99], considering different levels of thermal inertia [100];
4. scalability and applicability with respect to different types of end-uses [101] and multiple temporal [102,103] and spatial scales [104–108];
5. visualization of the impact of users' behaviour [98];
6. model robustness testing, under different behavioural conditions, using Monte Carlo simulation [99];
7. use of Bayesian analysis [109,110].

Different energy modelling approaches in the built environment are described more in detail in the next section.

## 3. Energy modelling in the built environment

Energy dynamics in the built environment can be described by means of different modelling approaches. Models can be used for multiple purposes and in multiple applications during building life cycle [111]. Modelling research, if properly oriented [17,112] can foster multi-disciplinary collaboration and the typical applications range from design phase simulation [75,77] to energy management, fault detection and diagnosis [113], optimal control [114,115], etc. Further, building energy models can be used in combination with other energy models (e.g. district or city energy models) to optimize interaction with infrastructures [38,116,117], or to analyze sectorial level policies [118]. In many cases, the underlying models can be formulated as optimization problems [64], i.e. simplified and with a transparent and explicit formulation of optimization objectives (e.g. energy, cost, emission, etc.) that can scale up to district [119] and city [120] scales. The fundamental goals of these models are sizing and defining schedules of operation [121] under economic and environmental constraints. When multiple objectives (more than two/three) or criteria have to be considered simultaneously, further simplifications are possible, like weighting different objectives with factors [122], or relying on boundaries given by data envelopment [123]. The use of appropriate simplifications and model reductions can ease the process of implementation and the use of robust and scalable computational techniques to respond to technical problems within the Internet of Things (IoT) paradigm [124]. In fact, IoT solutions could open up new perspectives related to data analytics in the built environment. However, the problem of modelling integration should be necessarily addressed by research to ensure the consistency of the proposed solutions with the needs at the technological and sectorial level [53]. In the following sections a synthesis of the state of the art of modelling is presented together with a discussion on some of the relevant challenges that energy modelling faces at present.

### *3.1. State of the art of energy modelling*

In literature we can find different papers depicting in detail the current state of the art of building energy performance modelling [118,125–127]. Further, a description of the evolution of research in the sector can be found as well [128–130]. A synthetic scheme reporting the relation among relevant categories describing building energy modelling approaches is presented in Fig. 2, considering general classification (top-down vs bottom-up) [131], technological and sectorial level perspectives (engineering, econometric, technological), model type (law driven vs data driven), and finally level of transparency with respect to the description of underlying phenomena, from more (white-box) to less transparent (black-box).

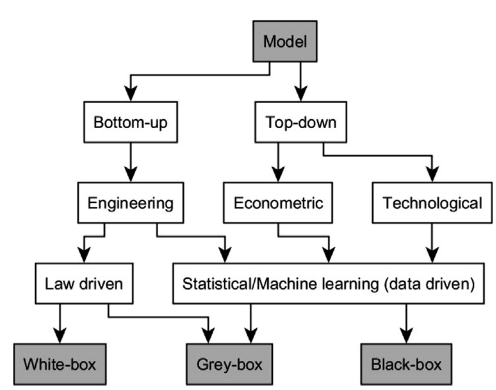


**Fig. 2.** Synthesis of the state of the art of building energy models.

What appears to be particularly important today is the possibility of selecting modelling approaches based on their suitability with respect to application criteria [73]. Further, it is necessary to establish boundaries for the validity and acceptability of models' results, for example using verification and validation standards [20,132], together with calibration protocols [133]. Additionally, availability of information, appropriate data/meta-data structures and software emerge as recurrent elements in recent research [17], indicating possible directions for future development. We can identify similar elements in literature envisioning the evolution of building energy models [134–136]. In this sense, it is also necessary to stress the importance of the ongoing research on automation systems in buildings, which can represent an enabling technology for detailed data acquisition and processing on a continuous base. However, there exist several issues limiting the development of innovative and cost-effective solutions in building energy management and automation systems [114,115], among others:

1. lack of model flexibility and customization to specific problems and conditions (need for parametric/probabilistic analysis in design phase and continuity with calibration in operation phase);
2. lack of coordination of models across life cycle phases;
3. lack of feedback to improve processes and technologies incrementally at multiple scales;
4. lack of use of technological paradigms such as IoT [124] and Linked Open Data to foster collaboration and emergence of innovative solutions from building data analytics.

In the next section research challenges are presented together with a selection of research features, considering transversal topic emerging from recent literature highlighting open questions [137–140] for future built environment.

### 3.2. Challenges for energy modelling

Energy efficiency increase strengthens the interdependency between design and operational optimization of systems (as it tightens performance boundaries), across multiple scales of analysis. This, consequently, determines the need for more formalized approaches to the use of optimization models in energy research and practical applications [18], together with a greater level of coordination and scalability in the underlying objectives, as mentioned before. Modularity, scalability and possibility of decomposition of energy models are crucial to reduce complexity and to obtain simple but reliable representations of real phenomena. We can ideally represent building energy behaviour across multiple scales of analysis (where energy and mass balance can be used as a scalable principle for model construction, verification, validation and, eventually, calibration), while maintaining a certain degree of alignment with respect to information. For example, we can view aggregations of building as loads for infrastructures (electricity, gas, water, district heating and cooling networks) and energy hubs/multi-energy systems [116,117]. We can also analyze building behaviour at the metre level (electricity, gas, water, heating and cooling) [25,141] or technical systems level (building services). Further, we can consider a subdivision up to the thermal zone level or even individual building components [101]. Finally, we can analyze the energy and mass balance of human body [142,143], with respect to activity and environmental conditions (i.e. embodying user perspective in modelling).

If model simplifications and approximations are correctly chosen, it is possible to quantify reliably energy fluxes at multiple scales, following the chosen hierarchical decomposition strategy and identifying useful insights that could orient further investigations with more detailed modelling approaches [144], where and when necessary. Examples in this sense can be found in literature for building components and thermal zones [145], technical systems [38] and interaction between buildings and infrastructure [116,117]. While having been created for different purposes, these examples highlight the possibility of integrating models at multiple scales of analysis and for different purposes, as proposed in recent literature [112]. Going back to applications, energy efficiency measures can create multiple advantages [7,8,55] and building sector potential is particularly relevant [22]. At present, both design and operation optimization in energy systems are active research fields. Among the most relevant issues studied in literature we can find at building scale:

1. techno-economic optimization strategies for integrated design of buildings [85];
2. optimization strategies for building operation [146,147];

In parallel, at district/neighbourhood and urban scales:

1. techno-economic design optimization of decentralized multi-energy system [35,36,119];
2. optimization strategies for decentralized multi-energy systems operation [116,117].

It is worth recalling the fact that, with respect to energy transitions planning, built environment can represent an intermediate scale of analysis, collocated between infrastructures and users/investors, according to Multi-Level Perspective planning framework. A tight integration and comparability among different models should be present as well to perform effectively multiple tasks in different building life cycle phases [111]. For this reason, we should be able to pass from models to simulated data (model output, forward approach) and from measured data back to models (model input, inverse approach), in multiple ways.

In terms of methodological approach, continuous improvement by learning from feedback is the key for evolution, because (in energy modelling) we generally rely on multiple simplifications and approximations that can be improved progressively, by acquiring new evidence. This principle can be incorporated in building energy modelling research by considering the possibility of using both forward and inverse modelling approaches in a synergic way [98,99], thereby establishing a continuity in the use of energy models across life cycle phases and across scales, considering the suitability of different modelling approaches, from white-box to grey-box and black-box [73]. A synthetic scheme representing an example of integration of forward and inverse modelling approaches for continuous improvement is represented in Fig. 3.

Hereafter, we present a selection of features that can be considered in building energy modelling research to address current and incoming challenges:

1. integration of multiple domains in terms of simulation capabilities;
2. separation of domain specific concerns and possibility to derive useful insights for more specialized analysis;
3. creation of a hierarchy in information and attribution of weights to different aspects (easing numerical and visual interpretation of results);
4. holistic perspective with integration of information at multiple levels;
5. creation of continuous learning and improvement cycles across building life cycle phases;
6. identification and selection of empirically grounded simplifications;
7. definition of transparent optimization objectives (i.e. energy, cost, emission, etc.);
8. consistency with state-of-the-art modelling in terms of validity, reliability, acceptability, suitability;
9. exploitation of scalable computing techniques and theoretical properties which enable faster calculations and guarantee optimality of solutions.

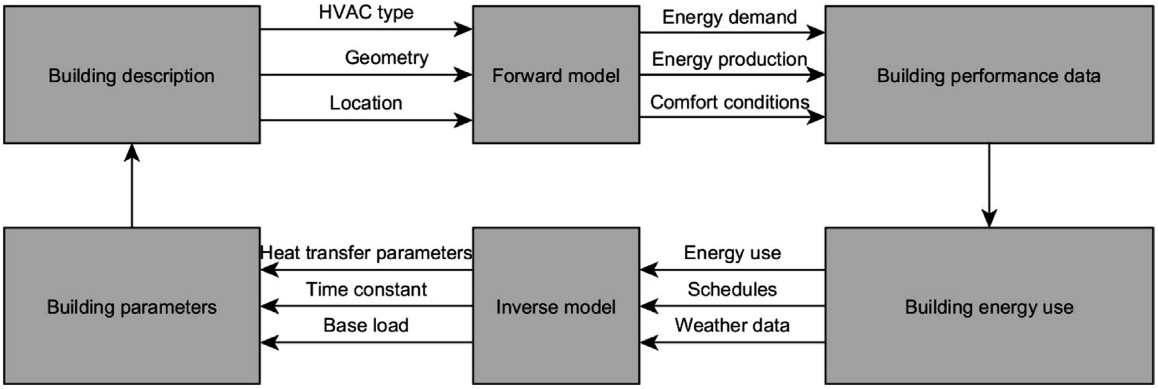


**Fig. 3.** Forward and inverse modelling integrated workflow (for continuous improvement).

**Table 1**
Urban scale analysis – Sustainable Energy Action Plans (SEAP).

| Urban indicators (SEAP) | Questions | Actions |
|---|---|---|
| **Energy demand** (Demand for energy carriers in the different final energy uses) | What is the expected final energy use of an urban area and the energy spent on different uses in kWh/year and per square metre? | Norms for spatial & urban planning with energy-efficient requirements<br>Standards & labelling<br>Tax reductions, tax credit, soft loans to fund energy-efficient actions |
| | What is the baseline energy performance of buildings and urban areas?<br>What is the heating/cooling demand for different energy carriers in kWh/year and per square metre? | Contractual agreements with Energy Service Companies (ESCOs) |
| **Energy supply** (Energy carriers and share of local energy from renewable energy sources) | What is the percentage of renewables in the total energy supply (%)? | Spatial & urban planning, considering RES integration<br>Tax reductions, tax credit, soft loans to fund energy renewable actions |
| | What is the annual amount of renewable energy produced with respect to the total energy supply?<br>What is the share of each technology in the annual production of renewable energy? | Contractual agreements with Energy Service Companies (ESCOs) |
| **Environmental impact** ($CO_2$ emissions and reductions compared to the baseline) | What are the total $CO_2$ emissions per year in a city district, in an urban area, and in specific buildings?<br>What is the difference in $CO_2$ emissions and in energy demand/consumption for different improvement scenarios compared to the baseline?<br>How to select the most convenient improvement, according to a set of indicators? | Multi-criteria analysis of different energy-improvement scenarios with respect to carbon emission |
| **Economic impact** (Energy costs/economics) | What is the cost of supply by energy carrier?<br>What is the cost of supply by final energy use for each dwelling, building or the whole area? | Tax reductions, tax credit, soft loans to fund energy-efficient actions.<br>Capital or operating grants and subsidies for low income households |
| | What are the investment and maintenance costs of the improvement scenarios?<br>Number of households in energy poverty?<br>Economic effort of energy consumption per household? | Feed-in tariffs<br>Subsidies for families at risk of energy poverty |

The importance of these features appears even more evident if we think about the problem of optimal interaction of buildings with infrastructures [11] both in a technological and sectorial perspective but also, more in general, if we think about new businesses enabled by data analytics in the built environment. In order to depict the potential of the combined use of data analysis techniques at multiple scales we report in Table 1 an analysis of indicators used in Sustainable Energy Action Plans [120], with respect to related technical questions and actions. The corresponding technical questions at the building level are reported in Table 2.

Techniques reported in Table 2 represent simply a subset of all the possible techniques that can be found in literature for these technical problems, but we can identify how multiple technical questions can be addressed by using the combination of a few computational techniques:

1. clustering [148,149];
2. piece-wise linear multivariate regression [47];
3. linear multi-variate regression [92,101];
4. time-series analysis [150];
5. model predictive control [146,147].

### 3.3. Techno-economic optimization issues

Economic criteria have to be always considered in modelling, to ensure the feasibility of technical solutions. However, in cost-optimal analysis of building systems [151] different criteria are considered simultaneously, because a simple minimization of initial investment cost wouldn't be appropriate to promote high efficiency solutions. From the technological point of view, buildings are composed by several subsystems, but optimized solutions, involving design and operation choices, have to account for the performance at the system level in its life cycle (or in an appropriate time frame of analysis). Primary energy, carbon dioxide emission and comfort are other essential categories of performance indicators to be considered in this sense, together with

**Table 2**
Building scale analysis – Technical questions and data analysis techniques.

| Questions | Technique 1 | Technique 2 |
|---|---|---|
| How can we aggregate geographically building data (e.g. aggregation of data at the district/neighbourhood and urban scale)? | Clustering | – |
| How can we aggregate non-geographically building data (e.g. aggregation of similar buildings in terms of shape, age, end use, business activity, etc.)? | Clustering | – |
| Which building parametric data (e.g., building characteristics, operational activities and occupant behaviour) is the most useful for predicting building energy use? | Multi-variate regression | – |
| How can we benchmark the relative building energy performance within the portfolio? | Multi-variate regression | – |
| What percentages of the total energy use are due to base load, heating use and cooling use, respectively? | Variable base degree-days (energy signature, piece-wise linear model) | – |
| What are the potential improvement opportunities? | Variable base degree-days (energy signature) | Multi-variate regression |
| How can we optimize the design of technical systems (using energy signature to improve design of technical systems)? | Variable base degree-days (energy signature) | Multi-variate regression |
| What are the root causes for less efficient buildings? | Variable base degree-days (energy signature) | Multi-variate regression |
| How can we discriminate weather dependent/independent behaviour, and perform improvement tracking and energy savings from retrofit activities? | Variable base degree-days (energy signature) | – |
| How can we detect abnormal energy use in the historical energy use data? | Variable base degree-days (energy signature) | Time-series analysis |
| How much energy do we expect to use in the future? | Variable base degree-days (energy signature) | Time-series analysis |
| How do we analyze the real operating conditions of building and people behaviour? | Clustering | Time-series analysis |
| How can we use MPC in buildings and positively interact with end-user (zonal modelling) and energy infrastructures (technical systems and metering problem, multi-level view)? | Time-series analysis | Model Predictive Control (MPC)/ Optimization |

initial investment and operation cost. Further, techno-economic evaluations can be conducted according to different perspectives. Private investors act according to a micro-economic perspective, trying to maximize the net present values of their investments (or other economic indicators) under constraints, while institutional actors and investors act, in general, according to a macro-economic perspective, looking at the whole system. This issue is particularly relevant for demand side management and energy storage systems, as will be discussed in detail in the next section. Additionally, energy modelling is multi-disciplinary and cross-sectorial and built environment applications can share, at least, a similar methodological approach with other sectors of final energy use, such as industrial processes [152] with respect to accounting, simulation and optimization models and tools. This is important, for example, if we think about the electrification of heat and mobility demands, together with the introduction of multi-energy systems [35] and energy hubs [36,37]. However, relevant specific issues for the built environment have to be considered. In fact, despite the technical potential and the possibility of defining metrics to evaluate problems transparently at multiple scales, the appropriate simultaneous consideration of multiple criteria in technological choices [122], on the one hand, and initial investment cost, on the other hand, remain critical dimensions: buildings are generally designed, constructed and operated by different entities (often with conflicting needs and different responsibilities) and conventional financing schemes are not generally appropriate in this sense, e.g. to account in detail for the investment risk determined by inefficiencies [88]. Costs across the building life cycle are distributed among different actors and processes (with different perspectives) because buildings are long-term assets. Further, people behaviour [98,99] and comfort preferences [98,153] constitute additional elements of uncertainty which are particularly relevant with respect to the interaction with infrastructures [154]. All these factors can lead to a consistent gap between predicted and actual performance, which should be properly considered and analysed [48,79].

## 4. Demand side management and energy storage systems

As described before, high efficiency building paradigms combine a drastic energy demand reduction with on-site or nearby renewable energy supply. Primary energy and emission factors coefficients [20] assumed in accounting the impact of delivered and exported energy from the building, as well as the normative requirements in terms of on-site and nearby energy production, will play an essential role for the evolution of the built environment, considering both code compliance and operation management. Of course, the increase of penetration of weather dependent RES will determine a considerable change in the weighting factors used for accounting the energy exchange with the grid [155], which depends on the ability of the electric system to use the energy produced in a specific moment in time (determining the need for a dynamic calculation and time-series data) as well as on the conversion efficiency of storage systems. As specified in the introduction, storage systems are essential to balance the mismatch between production and demand (load matching [141]), i.e. to decouple them temporally and spatially. Further, in the building sector, the increasing electrification of heating, domestic hot water and mobility demands is important to enhance the penetration of RES, but the seasonal distributions of heating and cooling demands (and the related needs for long-term storage) create bottlenecks for the deployment of conventional electric storage solutions, which are mainly conceived for short-term storage (daily/weekly). Therefore, in spite of the techno-economic feasibility of high efficiency new and retrofitted building, the positive effect of innovative practices at the sectorial level could be strongly inhibited by the absence of a proper co-evolution of built environment and infrastructures, in particular electric grid. Effective demand side management at the building stock scale can contribute to the increase of reliability and financial performance of electrical power systems [156].

### 4.1. Technological issues overview

In this section we consider the role of demand side management (DSM) together with that of energy storage systems. DSM refers to changes on the demand side of energy systems, considering both technological and behavioural changes, thereby including several different practices. Demand side management [157] should be the starting point in energy transitions, because demand reduction is crucial for creating more reliable and sustainable energy systems. From a systemic point of view, storage technologies can be described as elements that allow to store excess energy in time intervals with high production and low demand and that allow to restitute energy in time intervals with high demand and low production. Within DSM we can consider demand response (DR) strategies which are an adjustment of power demand obtained by load shifting and curtailment. From a conceptual point of view, DR can act in a similar way to energy storage, but has an important advantage. No actual charge/discharge process happens, as no conventional storage technology is involved and there is no impact of the material and resources used for the production of storage technology [158]. Substantially, DR acts in terms of load shifting for “peak clipping” (high demand) and “valley filling” (low demand) in load curves of electric system. The main weakness of DR is that the technical constraints, due to the temporal distribution of coupled processes, do not allow an unrestricted usage of its theoretical potential. In general, the result of DSM strategies depends on both technical potential and social acceptance and, therefore, it is important to understand the specific features of end-uses and their temporal scheduling. Further, DSM deployment should be supported by price-based or incentive-based schemes aligned with the policies' targets [159].

Additionally, the current evolution towards decentralized energy systems [35,36] implies the necessity of creating an interplay among different sectors of the demand and different energy carries. Of course, it is important to consider both the temporal and spatial distribution of demand (e.g. load profiles, load duration curves, etc.) and the proportion of the demand with respect to different energy carriers. A synthesis of the interplay among energy storage systems and energy carriers is represented in Table 3.

Actually, energy storage systems reported before are a combination of technologies, where both conversion and storage processes are present. Beyond electricity, the possibility to store energy in the form of fuels (hydrogen/methane) [32–34] or thermal energy (heating and cooling) [160] for a long-term, could open new possibilities for energy efficiency, considering the demand of energy carriers clustered on spatial and temporal scales. This highlights again the importance of the scalability of models, introduced in the previous section. In fact, in the definition of design and operation strategies, multiple perspectives have to be considered, from infrastructures (supply side) to end-users (demand side). A synthesis of the possible adoption of different energy storage systems is reported in Table 4 with respect to infrastructures and end-uses (sectors of demand). As described before, the spatial and temporal distribution of demand is crucial, as many of the technologies reported are suitable for short-term storage, while others are suitable for long-term storage. In particular, batteries can be appropriate to balance daily/weekly variations but they are not techno-economically feasible, at present, for monthly/seasonal storage, which could be necessary to enable further development of the high efficiency building paradigms (e.g. NZEBs), for the reasons outlined in the previous section.

Finally, conversion efficiency is another essential element to be considered in modelling. Sample data of conversion efficiencies for energy storage systems presented in recent literature are reported in Table 5.

**Table 3**
Energy storage systems and energy carriers interplay.

| Technologies | Carriers | | | |
|---|---|---|---|---|
| | Electricity | Fuels | Heating | Cooling |
| Pumped hydroelectric | X | | | |
| Batteries | X | | | |
| Other storage technologies (flywheels, supercapacitors, compressed air) | X | | | |
| Demand response | X | | | |
| Power-to-Hydrogen/Power-to-Gas | X | X | | |
| Power-to-Heat with thermal storage | X | | X | |
| Heat Pump with thermal storage | X | | X | X |

### 4.2. Technological and sectorial level complementarities

As already introduced, optimal design and operation problems are more and more integrated [35,173] and it is necessary to consider techno-economic optimization from multiple perspectives (macro and micro). As described in Section 2, strategies for energy transition are necessary from a systemic point of view (macro-economic perspective) but, with respect to energy efficiency practices, the point of view of investors has to be considered (micro-economic perspective). As introduced in Section 2.2, analysing purpose in technological and sectorial level complementarities is a matter of perspective (e.g. technological when the focus is reducing price or increasing performance, sectorial when the focus is societal needs through the eyes of policy makers or authorities). Clearly, different business models, in terms of fees, taxes and incentives, can open different scenarios with respect the design and operation of technologies. In fact, investors analyze business cases before investing and this type of investment has to be profitable over a reasonable time frame. The aggregation of prosumers on a local base (district/neighbourhood) could help finding economies of scale for the adoption of on-site generation and storage technologies integration in the built environment. These economies of scale are determined both by sizing optimization and by lower cost with respect to individual installations. As already described, cost-optimal analysis in Section 3.3 as well as other techno-economic optimization approaches consider generally multiple indicators such as cost, energy and emission simultaneously at multiple scales, from single buildings, to neighbourhoods and cities.

First, an important topic is the availability of updated dynamic time series data of primary energy and emission factors at national scale [174,175]. At the technological level, large scale deployment of storage requires overcoming current major barriers, i.e. the actual costs, material stability, reliability, durability, and safety [176]. Further, size and location of storage solutions constitute relevant constraints at building scale [164]. For example, at the building scale there can be an interplay between electrical and thermal storage options [177]. While there exist clear business models for electricity storage [178], this is not the case for thermal storage, considering in particular the regulatory environment and the cost of commodities [179]. Electricity storage planning is part of the evolution of infrastructures [180]; in this sense, analysing and predicting the mismatch between production and demand (and their cycles) [181] is crucial to determine the size and operational strategies for multi-fuel and multi-output energy systems [37]. The advantages offered by Community scale systems can be easily demonstrated [182] but the most important barrier for large scale storage deployment remains investment cost [183], considering also critically other sectorial barriers at the policy level [184,185], even though a decreasing trend in costs has been observed [186].

On the other hand, demand response and flexibility programs [187] rely on the predictive ability of building-to-grid models. Demand flexibility can be evaluated in terms of amount, time and power as well as cost. Moreover, when merging electricity and heat demand as for electricity-driven heating systems, a new degree of freedom is introduced. For this reason, a recent research proposed new performance indicators like the instantaneous power flexibility [188]. As already mentioned, Community scale solutions allows to benefit both from economies of scale and diversity of load profiles to smooth peaks and enhance performance [189], when high penetration of renewables happens [190]. Additionally, in terms of aggregation and diversification, it is important to consider concepts such as aggregators, virtual power plants [191], and prosumers [192]. The diversity of building operational profiles [193] should be considered in particular with respect to the thermal inertia of both building fabric and heat storage systems [194]. An additional element of uncertainty is given by the variability of building fabric performance in real conditions [195]. However, automation technology at the building scale can help reducing energy consumption while satisfying safety, comfort, and

 

**Table 4**
Energy storage systems with respect to infrastructures and end-uses.

| Technologies | Infrastructures | | | | End-uses | | |
|---|---|---|---|---|---|---|---|
| | Electric grid | Natural gas grid | Fuel supply | District heating/ cooling | Buildings | Industry | Transport |
| Pumped hydroelectric | X | | | | | | |
| Batteries | X | | | | X | X | X |
| Other storage technologies (flywheels, supercapacitors, compressed air) | X | | | | | | |
| Demand response | X | | | | X | X | |
| Power-to-Hydrogen/Power-to-Gas | X | X | X | | | | |
| Power-to-Heat with thermal storage | X | | | X | X | X | |
| Heat Pump with thermal storage | X | | | X | X | X | |

**Table 5**
Energy storage systems and efficiencies.

| Technologies | Efficiency | | |
|---|---|---|---|
| | Electrical % | Heat-recovery % | Round-trip % |
| Pumped hydroelectric | 87 [161] | – | 75–85 [162] |
| Batteries | 85 [163] | – | 75 [164] |
| Other storage technologies (flywheels, supercapacitors, compressed air) | 70–79 [165] | – | 54 [166] |
| Demand response | 70 [167] | – | 52 [168] |
| Power-to-Hydrogen/Power-to-Gas | 32 [33] | 50 [33] | 45–60 [169] |
| Power-to-Heat with thermal storage | – | 98 [170] | 98 [171] |
| Heat Pump with thermal storage | – | 95 [171] | 300[a] [172] |

[a] Heat pump efficiency is conventionally computed as COP [35] without considering energy extracted from air, ground, groundwater, etc.

productivity [196] requirements. Finally, an increasing quota of electric load from transportation at the building level should be accounted as well [197,198].

Going back to the sectorial level, the trade-offs between revenue and emissions determined by energy storage operation (e.g. due to low round-trip efficiency of storage) are another important factor [199] that has to evaluated together with the social opposition to capacity expansion [200], creating more coherent planning processes. Finally, in terms of performance metrics LCOE, acronym for Levelized Cost Of Energy and Electricity [201] and LCOS, acronym for Levelized Cost Of Storage [202,203] are generally used. An overview of values for LCOE metric for storage systems is reported in the next section.

### 4.3. Levelized cost of energy metric

In building thermal applications, the reference energy cost for storage systems should be in the range of 0.60–1.43 EUR/kWh [204]. Seasonal thermal energy storage with up to 2 cycles per year show performance around 3.00 EUR/kWh [205]. If the building is connected to a Community Energy System such as District Heating, the performance fits into the previously mentioned range [206]. When subsides or incentive schemes are set up, especially in the field of solar energy and electrical battery as storage option, currently the cost is between 0.74 and 0.98 EUR/kWh and decrease is expected for the next years leading to a range of 0.17–0.27 EUR/kWh [207]. In a PV battery system not all energy needs to pass through the storage, thus the resulting average cost of directly-consumed and stored electricity will be even lower. Without dedicated supporting tariffs, current battery module prices within optimized system configurations still do not lead to profitable investments such as Li-Ion batteries for solar energy storage with daily cycles of operation. However, batteries remotely controlled by an aggregator can help balancing daily renewable intermittency and their profitability can rises further [208]. Among battery technologies, Lead Acid battery in stationary systems are well-established but could be considered the past in comparison to new advanced hybrid Lead Acid Ultrabattery or other technologies, such as Nickel Zink (NiZn). Their LCOE is 0.81 EUR/kWh. Redox Flow battery can decrease the storage cost to 0.52 EUR/kWh and Lithium Ion even to 0.16 EUR/kWh [209]. The first one is not deployed on a large scale and is not established in the market while the second is mainly used for non-building applications.

On the other hand, an outlook of thermal energy storage in terms of costs can be interesting. The road towards well-insulated and low-temperature heated buildings offers the chance for small scale low temperature heat storage with capacity costs of 0.60 and 0.53 EUR/kWh for the closed and open system, respectively [204]. They can be considered affordable for the building sector, being in the range previously discussed. However, a large part of existing buildings does not comply with those temperature supply requirements and needs further adjustments in terms of space and construction implying additional investment costs. Indeed, there are thermochemical energy storage materials with potentially high energy density, i.e. up to 1510 MJ/$m^3$, and long-term storage ability, but not economically viable in buildings at present. Successful and high-performance ones show prices between 350 and 3600 EUR/$m^3$ at laboratory test scale. Those values are, then, doubled by installation of further components and associated inefficiencies such as heat exchangers and hydraulics [210]. The overall results they achieve (converted in EUR/kWh of stored energy) are far from the suitability range reported before. A complete heat storage system based on sensible heat technology costs from 0.1 to 10 EUR/kWh of capacity, depending on the size and the insulation technology. Conversely, better performing materials with high latent heat capacity, such as Phase Changed Materials (PCM), and Thermo-Chemical Storage (TCS) systems show relatively higher costs, due to the heat and mass transfer applied technologies. A system equipped with PCM technology ranges from 10 to 50 EUR/kWh whereas the TCS ones from 8 to 100 EUR/kWh [211]. Values of electricity and thermal energy storage cost are summarized in Table 6, linking them with research in electricity infrastructure including new factors and strategic enhancement as spatial distribution, dispatch mode and Grid interaction [212]. Indeed, IRENA report mainly dealt with battery technologies [213].

A further element of interest is observed in a research by NREL [214] that highlights PV plants designed with storage from the very beginning have a lower life cycle cost than PV plants where the storage is added in a successive phase. Therefore, the adoption of storage should possibly be considered among the design options from the very beginning.

## 5. Conclusion

Research and development in energy transitions should necessarily face techno and socio-economic problems. Energy use and technology

**Table 6**
Levelized cost of energy for building applications.

| Technologies | Electricity | | | Heat | | | Reference |
|---|---|---|---|---|---|---|---|
| | LCOEmin | LCOEmax | Constraint | LCOEmin | LCOEmax | Constraint | |
| | [€/kWh] | [€/kWh] | | [€/kWh] | [€/kWh] | | |
| Lead Acid Battery | 0.74 | 0.98 | Spatial | – | – | – | [207] |
| Nickel Zink Battery | 0.81 | 2.8 | Technology | – | – | – | [209,213] |
| Lithium Ion Battery | 0.16 | 2 | Lifespan | – | – | – | [209,213] |
| Redox Flow Battery | 0.52 | 4 | Technology | – | – | – | [209,213] |
| Aquifer Thermal Storage | – | – | – | 0.53 | 3 | Spatial | [204,205] |
| PCM-assisted Thermal Storage | – | – | – | 10 | 50 | Cost | [211] |
| TCS Thermal Storage | – | – | – | 8 | 100 | Cost | [211] |

affect sustainability in all its fundamental components, society, environment and economy. Conventional energy planning and technological learning models are not sufficient because of their inability to deal with issues such as the behaviour of consumers, prosumers and investors, as well as the institutional factors driving decision-making processes, especially at the local and individual level. Further, the fast evolving technological landscape creates additional complexity and these issues inherently highlight how built environment could represent a suitable intermediate scale of analysis in Multi-Level Perspective planning of energy transition, being collocated among infrastructures and users. Research should be done to indicate possible innovation pathways for the co-evolution of built environment and infrastructures, starting from the current state of the art of multi-scale energy modelling. In this sense, the concept of analysis of complementarities is particularly powerful.

Optimal design and operational choices at the building level are systemic, to accomplish the presence of multiple technologies and needs, but buildings are, at the same time, nodes in infrastructural systems. It is particularly important to investigate the spatial and temporal scalability of modelling techniques by means of transparent metrics and KPI; in this paper we highlighted the scalability of techniques for techno-economic optimization and the scalability of inverse modelling techniques for model calibration aimed at energy management. Models can be improved on a continuous basis, considering forward and inverse approaches integration (i.e. using them in multiple applications during building life cycle), using validation and calibration standards at the state of the art. However, specific issues have to be considered for built environment applications. Buildings are long-term assets and, for this reason, it is necessary to establish a methodological continuity among modelling practices for optimal design and operation (as indicated before), aimed at reducing the gap between simulated and measured performance of buildings.

The role of models in the energy field is cross-sectorial and the use of common principles and techniques could stimulate a rapid development of multi-disciplinary research (e.g. multi-model "ecologies", open data, etc.), which is an essential part of innovation. Modelling research should provide useful insights on problems, accommodating multiple perspectives of stakeholders involved in decision-making processes. Again, this is particularly evident with respect to the problem of storage in energy systems with high penetration of RES, whose scope is, substantially, the spatial and temporal decoupling of energy supply and demand. Finally, the potential synergies among energy efficiency measures, renewable energy technologies, demand side management and storage systems at the sectorial level are evident but we need to be able to propose market effective solutions that can minimize the life cycle economic and environmental impact and, at the same time, that can represent a good compromise with respect to the different perspectives of stakeholders, in terms of socio-technical acceptability.

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