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Next frontiers in energy system modelling: A review on challenges and the state of the art

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ABSTRACT

Energy Systems Modelling is growing in relevance on providing insights and strategies to plan a carbon-neutral future. The implementation of an effective energy transition plan faces multiple challenges, spanning from the integration of the operations of different energy carriers and sectors to the consideration of multiple spatial and temporal resolutions. In this review, we outline these challenges and discuss how they have been tackled by the current literature, as well as pointing at directions for future research. Many of the existing reviews identify a list of challenges common to most models, but they tend to be grouped according to type or energy carrier. Here we take a new approach and structure both well-established models and solution approaches along with the main challenges that energy modelling will have to deal with in the near future. We focus on four main current challenges that energy system models face: time and space; uncertainty; multi-energy; energy behaviour and energy transition. The main findings suggest that: demand-side management applied to multi-carrier energy system models lacks; prosumers is explored only in a limited manner; general, multi-scale modelling frameworks should be established and considered both in the dimensions of time, space, technology and energy carrier; long term energy system models tend to address uncertainty scarcely; there is a lack of studies modelling uncertainties related to emerging technologies and; modelling of energy consumer behaviour is one of the major aspect of future research.

1. Introduction

The adoption of the Paris agreements by a large part of industrialized nations has raised the call for drastic cuts in greenhouse gas (GHG) emissions in the near future. Among the sectors involved, the energy system represents one of the major challenges for this green transition due to its heavy reliance on fossil fuels. The challenges featured in this sector need to be considered in future approaches on modelling the energy system in order to adequately support policy making. The first systematic energy system model was presented by Barnett in 1950 [1]. Nowadays, a large body of literature testifies the emphasis that has been placed over the years on this subject. See Table 2 for a non-comprehensive overview of reviews. Nevertheless, this arsenal of models and modelling frameworks has not proved mature enough to cover the possible future challenges that the energy system will be facing, such as the management of multiple carriers or the integration of multiple sectors. The increased pressure in decarbonizing the energy system has renewed the interest in energy system modelling, with several reviews trying to convey a comprehensive description of the utilized methodologies as well as providing new insights on how they can be used to answer new questions. Pfenninger et al. [2] group available models into four categories, "energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios", discuss a set of challenges these models are facing and identify future research needs. Hall and Buckley [3] provide an overview of the prevalent energy models used in the last decade in the United Kingdom (UK). They develop a classification scheme with the aim to make the model landscape more perspicuous and use it to classify 22 models for the UK. A similar approach is taken by Lopion et al. [1] who characterize 24 national energy system models. They identify trends

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Table 1
List of abbreviations.

Abbreviations	
CCS	Carbon capture and storage
CCUS	Carbon capture, usage and storage
CHP	Combined heat and power
DSM	Demand-side management
EV	Electric vehicle
EVPI	Expected value of perfect information
GHG	Greenhouse gas
IRES	Intermittent renewable energy sources
MCA	Monte Carlo analysis
MGA	Modelling to generate alternatives
MES	Multi-energy systems
MILP	Mixed integer linear programming
ML	Machine learning
PV	Photovoltaic (solar)
RES	Renewable energy supply
RO	Robust optimization
STET	Socio-technical energy transition
SP	Stochastic programming
VVS	Value of stochastic solution

and challenges in energy system modelling, with decarbonization and renewable integration seen as the major drivers. Ringkjøb et al. [4] review a large number of currently used modelling tools, ranging from small-scale power system models to global long-term energy system models, concluding that there are still various challenges when it comes to modelling future interconnected energy systems. Fattahi et al. [5] assess emerging challenges in the modelling of low-carbon energy systems resulting from the increasing share of variable renewable energy sources, increased complexity, and the demand for system integration. The review by Wiese et al. [6] also aims at providing an evaluation scheme for energy system modelling frameworks relative to a set of modelling challenges.

The interaction between multiple energy carriers is increasingly important, a perspective that is particularly emphasized in multi-energy systems (MES) modelling [10], which can be seen as a direction within energy system modelling. Multi-energy systems approaches seek to capture several energy sectors within the system boundaries. Mancarella [15] provides a solid introduction to the concept and a comprehensive overview of available models as well as assessment techniques to analyse them. In a second review, the authors point out some of the modelling challenges, particularly emphasizing multi-criteria decision making, spatial and temporal dimensions, and data management [14]. Both these reviews point at energy hubs, introduced in Favre-Perrod et al. [16] and analysed in [17], as an important concept in the multi-energy perspective. A comprehensive review on energy hubs is provided by Mohammadi et al. [13], while Reynolds et al. [12] reviews operational optimization of multi-vector district energy systems. In addition to energy hubs in the context of multi-energy systems, Hosseini et al. [8] review the role of multi-energy networks in providing flexibility of operation, security of supply and affordability in future energy systems. Kriechbaum et al. [11] evaluate three open-source modelling frameworks considering electricity, natural gas and district heating networks under five modelling criteria (modelling scope, model formulation, spatial coverage, time horizon and data) and three grid-specific modelling criteria (level of detail, spatial resolution and temporal resolution). While Kriechbaum et al. [11] take an integrated model perspective, Guelpa et al. [10] present technologies and modelling techniques for each of these three energy carriers and discuss trends towards integrated systems which drive a need for more research on new modelling methods. Groissböck [9] puts further emphasis on the open-source perspective, by assessing 31 different energy system modelling frameworks and concluding that open source models are not in general less mature in terms of functionality than proprietary or commercial models. The recent review by Prina et al. [7] identifies resolution, both in time, space, techno-economic detail and sector coupling, as the main challenge in bottom-up energy system modelling. They conclude that the simultaneous achievement of high resolution in all these fields is not yet reached by any of the 9 long-term modelling frameworks they analyse.

Nine of the listed reviews identify important challenges for energy system or MES modelling, either as a corner-stone of the review like in Pfenninger et al. [2], Wiese et al. [6] or as part of the motivation or discussion as in Lopion et al. [1], Groissböck [9]. Despite minor deviations in the exact phrasing used, the reviews show wide consensus on the major challenges for energy models ahead, see Table 3 for an overview. A successful transition to a low carbon energy future requires a good understanding of the dependencies of the different energy carriers and their integration, which is further complicated by systems operating at different scales, both time and space-wise. As a mention, electricity needs to be balanced on a very short timescale, while natural gas transport is typically modelled on lower time resolution. Likewise, different energy carriers might be modelled using different spatial resolutions, depending on their geographical availability or consumption pattern. Uncertainty poses another major challenge in energy systems modelling. The different drivers affecting the supply and demand of energy carriers have uncertain developments over long time spans. Forecasts only offer a mild idea of how the future key parameters may unravel. Therefore, special attention needs to be put on including uncertainty in energy systems models if they are to be used in long-term policy-making and investment planning. Finally, important changes in the energy system are likely to reverberate into society. For this reason, when modelling the future energy system, it is important to incorporate social aspects and behavioural elements which strongly affect the energy system development and energy transitions.

Although many of the reviews identify these challenges, they mostly focus on classifying a given selection of modelling frameworks or review trends and modelling techniques presented in the literature. Such reviews adopt a traditional approach, by grouping modelling frameworks according to the type of energy carrier. The review proposed in this paper aims at identifying four main modelling challenges that energy system models face: a) the handling of several energy carriers within the system analysed, both regarding sector coupling as well as multiple carriers at end-use level, b) the integration of different scales regarding time and space, c) how uncertainty is dealt with and d) the integration of energy transition dynamics and energy behaviour in models. This review analyses how these challenges have been addressed in the literature, and discusses which gaps should be covered and what is needed to advance the energy systems modelling research. The focus on modelling challenges as a way to classify the available literature and discuss the existing gaps, is novel compared to the traditional approaches. In addition, the holistic approach to address and interconnect four challenges within the same review is novel compared to the more specific approach adopted by other works that focus only on individual challenges. If energy systems modelling is to support the transition to a greener economy, these challenges need to be addressed. It is important to delve deeper into the sea of modelling techniques and solution approaches used to address the aforementioned challenges. This review aims at providing an extensive overview of models, modelling frameworks and methods dealing with these major challenges in different ways to enable model developers as well as analysts to advance energy systems modelling beyond today's state of the art. The main focus is bottom-up models and modelling frameworks for energy systems in developed countries. We will not discuss transparency issues, as this aspect is not only related to energy system modelling, and hence is outside the scope of this work. In addition, there is scientific literature which already discusses such issues in depth, such as [18,19]. In the remainder, Chapter 2 discusses models, modelling frameworks and new approaches to deal with multi-energy systems and flexible end-use, Chapter 3 provides insight into how different scales in time and space can be addressed and which models have successfully done so, Chapter 4 reviews four different

Table 2
Relevant reviews in the literature.

Prina et al. [7]	Challenges related to resolution in energy system models
Hosseini et al. [8]	Multi-energy networks
Fattahi et al. [5]	Modelling challenges in low-carbon energy systems
Groissböck [9]	Open source energy system models
Guelpa et al. [10]	Infrastructure for MES
Kriechbaum et al. [11]	Grid-based MES modelling
Lopion et al. [1]	Classification of energy systems models and discussion of trends and challenges
Reynolds et al. [12]	Modelling techniques for operational optimization of district MES
Ringkjøb et al. [4]	Classification of energy and electricity system models with high shares of RES
Wiese et al. [6]	Evaluation approach for energy system modelling frameworks
Mohammadi et al. [13]	Energy hubs for integrated management of MES
Hall and Buckley [3]	Review and categorization of energy system models in the UK
Mancarella et al. [14]	Drivers, requirements and opportunities in MES modelling
Mancarella [15]	MES models and assessment techniques
Pfenninger et al. [2]	Trends and challenges in energy system modelling

Table 3
Challenges in energy systems or MES modelling according to nine existing reviews, with an indication of the number of reviews mentioning each challenge. Challenges suggested by a single review not listed.

Time & space	9
Uncertainty	6
Multi-energy	6[a]
Energy behaviour and energy transitions	5
Transparency	4[b]

[a]Additionally two reviews on MES have multi-energy as an underlying assumption for the whole review.

[b]Additionally two reviews discuss the more limited topic on the openness of data collection and management.

approaches on how uncertainty can be addressed in energy systems modelling and Chapter 5 elaborates on the ways that social interactions, energy transition dynamics, and energy policies and politics can be integrated into energy systems modelling. The insights are discussed in the light of what is needed to advance energy systems modelling to be fit for the transition to a clean future energy system. A list of abbreviations used in the paper is provided in Table 1.

2. Multi-energy systems

Providing successful strategies to the energy transition requires a representation of the inter-dependencies among multiple energy carriers. Fig. 1 depicts key technologies and coupling points in modelling multi-energy systems. For example, the joint modelling of electrical and gas networks synchronizes peak loads in the power system with gas-network operations, resulting in more intensive use of the gas network. In this review, we define a model or modelling framework to be multi-carrier if it represents not only energy sources as primary inputs but also models the conversion and the end-use. Specifically, a multi-carrier model should represent at least two carriers at the end-use. Based on this definition, well-known modelling frameworks that cover three carriers (gas, electricity, and heat) are for example GENeSYS-MOD [20,21] and TIMES [22]. These modelling frameworks provide a long-term perspective of Pan-European energy-transition strategies considering generation and transmission expansion but have an aggregated representation of short-time resolution and technological details. This is a contrast to the METIS model [23] which provides a more detailed short-term analysis and better technological representation of the carriers but no long-term endogenous capacity options. The EnergyPLAN [24] and ReMOD [25] modelling frameworks also feature strong technological detail and multiple modelling capabilities while taking into account long-term investment decisions. However, EnergyPLAN and ReMOD are better suited for national energy systems compared to the PRIMES model [26] which has equal capabilities and slightly less technological detail. PRIMES covers multiple end-use sectors as well as carriers in detail and represents the Pan-European energy-economic system. Lastly, the ESME modelling framework [27] provides a new dimension of capabilities: such as uncertainty modelling considerations, a higher level in the disaggregation of the energy sectors, details in network transmission assumptions and certain aspects of system security.

All in all, multi-carrier models have a trade-off between the level of engineering technological detail and temporal resolution (long term perspective for capacity expansion vs short-term representations of hourly supply–demand operations). Fathtabar et al. [28] find a balance in representing more detailed characteristics of power systems (e.g. AC load flow) coupled with gas and heat energy systems. There, a commonly applied approach to model such couplings in multi-energy system models is through the use of energy hubs, e.g., [13,29,30]. The hub typically receives energy through a set of carriers and contains conversion and storage facilities used to cover (by means of least-cost generation) the demand for, e.g., heat, electricity and natural gas for a certain region over a time period. However, the concept of energy hubs is more frequently used in local or district scale contexts compared to models and modelling frameworks with intercontinental or national coverage (e.g. METIS or ReMOD).

2.1. Modelling heat-electricity systems coupling

Coupling heat and electricity occurs at specific conversion points, identified as combined heat and power (CHP) power stations, electrical boilers, storage, or similar (see Fig. 1). It takes mainly into account the possibility of delivering heat, alongside electricity. For example, Konstantakos et al. [31] analyse policy incentives for CHP investments by looking at fluctuations in natural gas prices and calculating revenues from heat and electricity delivery. The IMAKUS modelling framework [32] accomplishes a heat-electricity coupling by having a unit commitment model combined with the use of CHP plants and electrolysers to transform geothermal fuels, biomasses, oil, gas, coal and lignite into electricity and heat. Similarly, the BALMOREL modelling framework [6,33] considers various fuels such as biomass, municipal waste, geothermal energy, and hydrogen in the production process, and defines a combined output of electricity and heat. Another alike model, Dispa-SET model [34], applies also a unit-commitment model to the power system while coupling heating constraints for CHPs, heat storage, and power-to-heat options. Likewise, the Oemof modelling framework [35] considers the same features but has the additional option to consider investments. These are 'single' period investments compared to other approaches that have multiple investment periods. For example, the ENERTILE model [36] includes decentralized heat pumps and district heat grids for long-term analyses of the Pan-European energy system. It provides more insights by incorporating heat grids that have the option to invest in heating technologies, hence corresponding decisions in line with the power system capacity expansion.

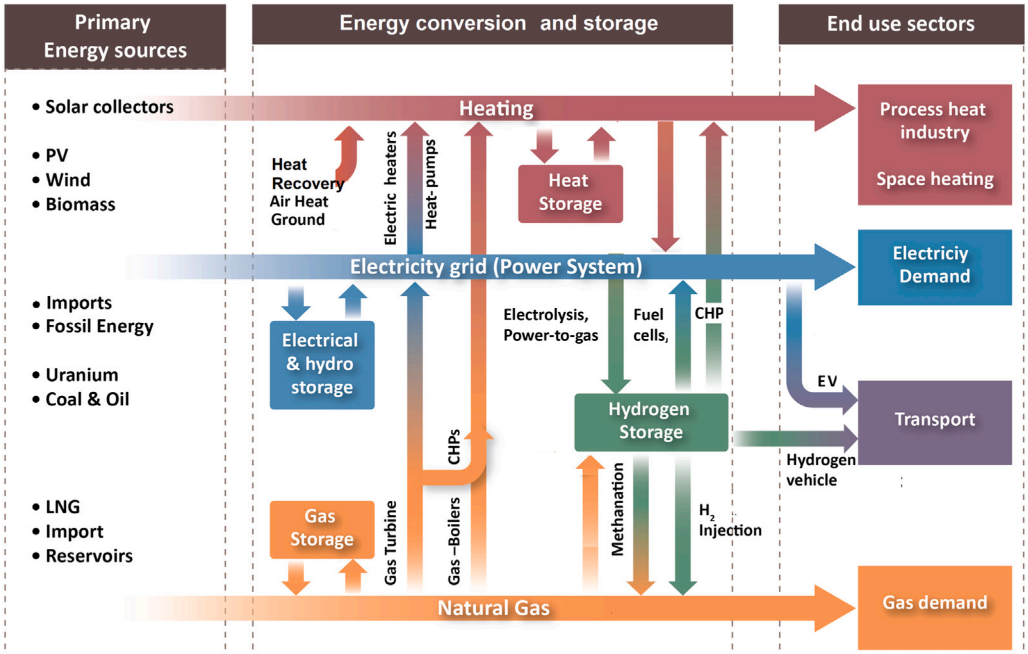

Fig. 1. Overview of modelling multi-carrier systems, main components and features.

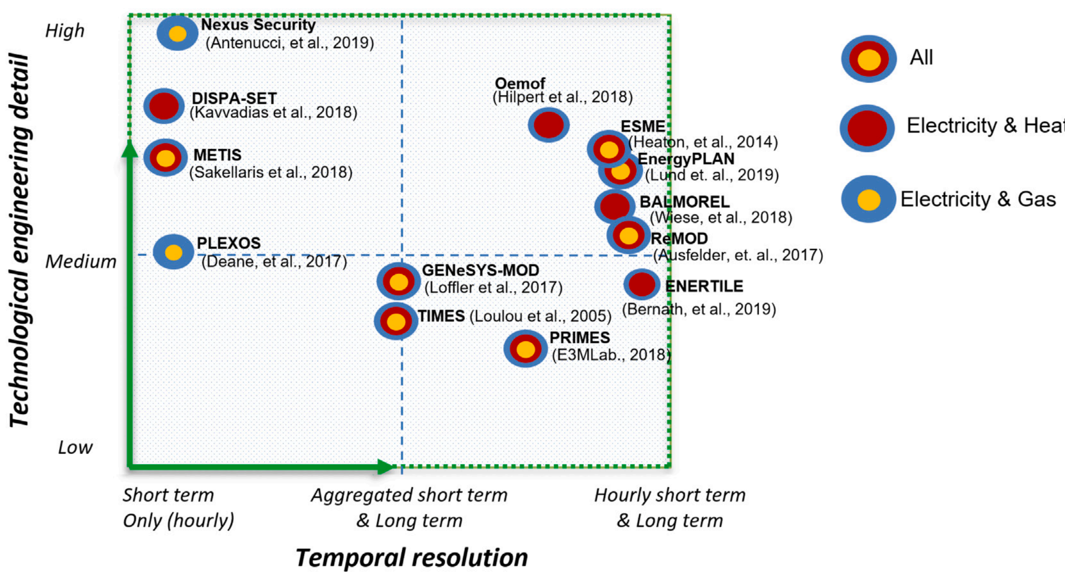

Fig. 2. Key energy system models considering at least two carriers.

2.2. Modelling gas–electricity systems coupling

Energy systems dealing with a high gas demand are typically modelled in much detail regarding engineering properties. For example, [37,38] study the optimal operation of gas-fired power plants while assessing the security of energy systems and the effects of natural gas networks on the optimal operation of gas–electricity systems. Aside from reliability or engineering perspectives, recent models have addressed long-term planning dimensions in gas–electricity systems [39]. For example, the structure of the RAMONA [40], GGM [41] or the Calliope modelling frameworks [42] features long term planning aspects of the gas infrastructure, but the models do not encompass a detailed technological representation of the gas system as such. In contrast, Antenucci et al. [43] provides a more engineering-wise detailed, coupled electricity–gas model which is linked to a long-term capacity expansion model. The authors consider gas storage such as line packs and other gas flow modelling features. Also, they perform an N-1 system analysis to check the failure in both energy system components. This is applied to the UK system where gas compressors play a role in coupling the carriers as they use electricity for gas operations. Similar methods on combining mathematical models of both systems are explored in [44–46] where the usual approach is to model gas–electricity network systems by representing the gas flow and DC power flow equations. In these papers, the inter-dependency assessment indicates that the consequences of failures in the power system could cause much more damages to the gas network than vice versa.

Overall, most of the gas–electricity models tend to focus on interdependency issues under a system security perspective and are limited on representing investment decisions (long-term). Modelling approaches are typically applied to IEEE test cases with a focus on short-term operations at the national level. In contrast, Deane et al.

[47] focus on policy and market implications based on an integrated electricity and gas model for the EU-28. There, various scenarios test the potential economic impacts of gas markets limitations (also refer to [48] for a perspective on combining gas and electricity markets). In short, when coupling both carriers the link (coupling point) is weak from the power system perspective while gas is more dependent on power system operations. Fig. 2 illustrates prominent energy system models covering heat, gas and/or electricity in terms of technological detail versus the capabilities on time resolution. Note that the positions of the models in the figure is approximate and that the list is not exhaustive.

2.3. Hydrogen and natural gas with carbon capture and storage

The design of nation-wide carbon capture and storage (CCS) value chains to curb gas CO_2 emissions has received considerable attention. The model by Klokk et al. [49] analyses the CO_2 value chain on the Norwegian continental shelf storing CO_2 in both aquifers and oil fields for enhanced oil recovery. The model finds an optimal CO_2 transportation network from a fixed set of CO_2 emission points and a set of potential injection sites. The arcs between the nodes are predefined and the model decides on pipeline size and investment year. Similarly, Hasan et al. [50] develop a model for developing a carbon capture, usage and storage (CCUS) network. However, contrary to the study by [49], it does not consider CO_2 hubs and transport from the sources to the hubs and from hubs to the storage. Hasan et al. [51] develop the framework in [50] further using a multi-scale approach for choosing the optimal materials and processes for the condition of each individual CO_2 source.

Regarding hydrogen value chains, Seo et al. [52] investigates the H_2 infrastructure for fuel-cell electric vehicles. They focus mostly on storage and transport of hydrogen using different transport means like compressed H_2, liquid H_2 in pipelines, trains or trucks while the energy carriers for production were assumed to be available only at certain nodes. Tso et al. [53] develop a multi-carrier energy model comparing different options for energy storage and transport of electricity through hydrogen. Their model includes ammonia and methanol as additional hydrogen carriers. It decides if it is beneficial to generate renewable electricity in regions with poorer yield and direct usage and storage without transport, or in regions with higher yield and long-distance transport. Similarly, Reuß et al. [54] look at a hydrogen supply chain in Germany. There, hydrogen production from renewable energy sources at the German coast is combined with demands in regions without the possibility of large-scale renewable energy generation.

A research gap in this stream of the literature is that combined natural-gas and CCS value chains, together with H_2, is less explored. Moreover, there is a lack of integration of such value chains within MES models. As one of the few examples, Sunny et al. [55] develop a H_2–CCS value-chain modelling framework based on the concept of resource task networks. It allows for the specification of exogenous end-use demand that can be satisfied using hydrogen and other alternatives. It determines the optimal H_2 and CO_2 infrastructure, including the production of hydrogen. CO_2 and H_2 hubs can exist, and the modelling framework investigates the optimal hub location. Differentiating between investment periods and standard periods, demand variations depending on, for example, seasonal or daily requirements can be included.

2.4. Demand representation

Long-term energy demands drive investment decisions in energy infrastructure and technologies. The quality of the results from energy system models thus relies on demand projections and their spatial and temporal features. End-use of energy is most commonly represented in energy system models through a set of nodes with a demand for a certain energy carrier or as an energy-service demand, e.g., [11,56]. These nodes arise from the spatial resolution in the model, selection of sectors included such as the residential, commercial, industrial and transport sectors, and the diversity of energy carriers absorbed in the considered sectors.

In this body of the literature, demand-side management (DSM) has been recently included due to its importance for accommodating intermittent renewables [57]. Sectors with DSM potential include residential and commercial buildings with heating and cooling demands, plug-in electric vehicles (EVs) [58] and power-intensive industries [59]. These sectors have gained relevance to balance RES and, along with the increasing integration of multiple energy carriers create new opportunities for DSM and load flexibility. One example is DSM for industrial, commercial and residential heat supply which may be provided by several energy carriers, including heating grids, which is commonly not modelled in MES models. MES systems with end-users that can switch between heat provision from different carriers can thus broaden demand-side services and accommodate curtailments in supply by several carriers. This could promote a low-carbon heat supply, particularly for heavy industries. Even though DSM has been explored for multi-energy systems, the research in this area appears more focused on technological feasibility and at the local scale [60], typically resorting to an energy-hub approach [61].

In general, DSM is mostly applied to power system models. Zerrahn and Schill [62] present a linear model for DSM with maximum hourly load shifts based on the ELIN modelling framework developed by [63]. It requires coverage of the total demand over the considered time window but resolves the issue of overestimated DSM effects observed in the DSM implementation in [63]. The latter was caused by allowing DSM units to shift demand up and down at full capacity at the same time. The DSM representation in [62] is implemented in the DIETER modelling framework by Zerrahn and Schill [64] to explore optimal storage capacity and flexibility options in Europe in 2050. Babrowski et al. [58] consider DSM with load shift by EVs in the PERSEUS-NET-ESS model, allowing charging of a certain share of the EV fleet to be shifted within a single day, but requiring that electricity needed for driving at a given day has to be charged on that very day. Marañón-Ledesma and Tomasgard [65] implement DR in the EMPIRE modelling framework [66,67], distinguishing between partially flexible loads, shiftable loads whose total energy over a certain horizon must be retained, curtailable loads and interruptible loads. Johnston et al. [68] implement DSM in the Switch model as price-driven inter-hourly load shifting. Panos et al. [69] include DSM in the Swiss TIMES model studying shifts of electricity demand for water heaters and heat pumps. They also allow load flexibility only on an hourly intra-day basis. This is also the case for [70] that incorporates DSM in the TIMES model for the French power system, distinguishing between residential-type devices that can be curtailed for short sub-hour periods and industry processes and EV loading that can be shifted between hours. Li and Pye [71] implement a rather comprehensive DSM representation for EVs and smart electric appliances in the UK TIMES model. They use a parameterized representation of shiftable potential for different appliances, with constraints on intra-day load shifting, allowing the load to be shifted up to given capacities and between permitted hours.

Compared with DSM with load shifting and possibly curtailment, some end-users of energy may also sell and supply surplus energy back to a local energy market. This type of prosumage is most commonly addressed for electricity, particularly from solar panels, and industrial sites engaging in energy arbitrage options. Integration of prosumage is generally lacking in most long-term energy system models [65], while a few exceptions exist. [72] includes an implicit prosumage concept from PVs in the DESSTINEE model, incorporating residential batteries that are charged once generation from the PVs exceeds household consumption and discharged otherwise, i.e., no electricity is exported to the grid. [73] incorporates prosumers with surplus electricity from PVs in the DIETER model ling framework. By including prosumer battery storage together with PVs, they enforce energy balances that allow generated electricity to be self-consumed, stored or sent to the market.

In summary, short-term volatility in loads, for instance by regions with a dense population of EVs or harbours with electric charging of ferries, are important aspects to consider in multi-carrier energy system modelling. The challenges are naturally connected to the time-spatial resolution representation in long-term planning models.

While the main advantage of modelling multi-energy systems is the possibility to include and compare several technologies at once, the main disadvantage is linked to the computational complexity that arises when different technological details have to be modelled. This leads to the challenge of finding a suitable trade-off between the in-depth representation of certain technical details and the approximation of other ones.

3. Time and space

Several trends in the energy system development challenge both spatial and temporal resolution of energy systems models that often have a wide spatial and temporal coverage to support analysis of policies and investments. Generation from intermittent renewable energy sources (IRES) can be variable during short time intervals, requiring a fine time resolution. Both distributed IRES generation and demand-side management give a decentralization trend that drives a finer spatial resolution. Furthermore, different energy carriers have different ranges and variability, e.g. the global commodity natural gas versus the local commodity heat, so that the modelling of multi-carrier systems involves handling different needs in resolution and coverage. These simultaneous needs for both high resolution and coverage impacts model size and computational tractability.

Various approaches to resolve this tension between model detail and computational tractability have been devised in the literature. Nevertheless, the trade-offs made in the treatment of data and modelling choices can impact the model results, as shown by Merrick [74], Shirizadeh and Quirion [75] with analyses of different ways to model different temporal scales. In this section, we discuss different approaches to model different temporal and spatial scales. In energy systems modelling, a sharp line between modelling and data can sometimes be hard to draw, however we will discuss matters primarily related to the treatment of input data in Section 3.3 and matters concerning modelling choices in Section 3.4.

3.1. Spatial resolution in energy system models

Most energy system model reviews provide information on the spatial coverage but neglect information on the spatial resolution, with the only exception of Lopion et al. [1] which classifies the models based on their flexibility in including a variable number of spatial nodes. In this review, we are interested in typical resolutions commonly used, as summarized in Fig. 3.

Single region models are relatively common [71,76–79], while models with more than a single region are categorized according to different division criteria. Many of these models have well established spatial divisions, often defined by public institutions, therefore forming what we define as *energy system independent divisions*. Examples of these sorts of divisions can be found in quite a large body of literature which, using different drivers, all come to a predefined division of the geographical scope [34,36,52,58,66,80–82]. These spatial divisions are typically not designed for energy system purposes, and do not necessarily fit well to energy system properties. Another strand of literature defines the spatial resolution based on *energy system driven divisions*, i.e. in relation to energy systems phenomena or properties, such as price zones [83], mixture of price zones and hydropower availability for the Nordic market [84] or onshore and offshore regions to capture the different resources availability [27]. [6,33] combine national resolution for overall economic aspects with regional (sub-national) resolution for the electricity system and area (sub-regional) resolution for the heat system. Other models, primarily focusing on the power system

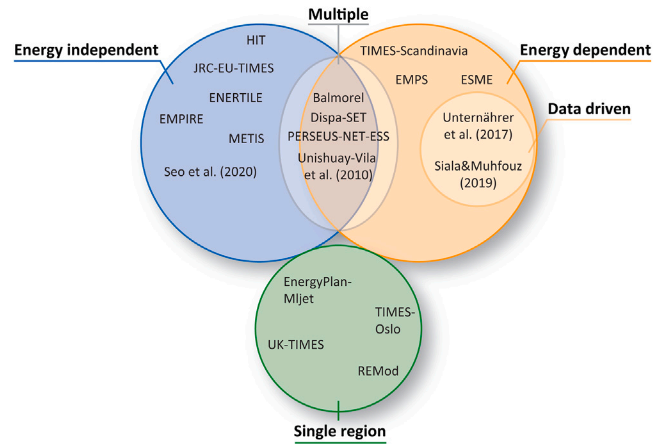

Fig. 3. Main approaches for defining spatial resolution, including model examples.

combine a regional division with unit level representation of power plants [34,58,84], or consider a multicarrier expansion combining regionally divided demand with unit-level expansions Unsihuay-Vila et al. [39]. Recent literature suggests defining a division based on the clustering of renewable resources [85,86] or demand [85–87]. Some authors discuss criteria for the definition of the spatial division of a model, each coming with different key dimensions [86,88], agreeing on some drivers such as the availability of natural resources, the cost of technology and the location of demand. Most importantly, geographical divisions should be made in order to obtain areas that should be internally homogeneous and externally heterogeneous. Case studies tend to support this claim. As a mention, Dorfner [89] provides analyses based on these data-driven spatial divisions and compares them with model results with country division. The authors point out that the choice of data for clustering influences what part of the energy system is represented the best, and recommend using transmission bottlenecks as clustering criteria for transmission infrastructure studies. Jalil-Vega and Hawkes [82,90] perform a set of analyses on the different results obtained with varying granularisation of the spatial scale. They observe that the results on heat network uptake differ up to 30% between the finest and coarsest spatial resolution, and that the largest differences were observed in heterogeneous areas. Shivakumar et al. [91] propose a clustering methodology for land use analysis in integrated land-energy-water modelling using the open-source framework OSeMOSYS. The purpose is to better explore the inter-sectoral linkages between the energy, land-use, and water sectors. Another relevant case in the spatial resolution domain is the model proposed by Moksnes et al. [92], which combines geospatial electrification algorithms (from OnSSET), with long-term spatially-aggregated bulk electricity supply modelling in OSeMOSYS. Simoes et al. [93] study the importance of spatial resolution for renewable sources integration. They observe that the spatial resolution has small effect on the whole energy system, but does affect the amount of wind and solar generation in relation to their cost-effectiveness and to the climatic conditions in the region where they are installed. A quite dissonant opinion is the one raised by [94], which questions whether the increased level of detail translates into a higher descriptive accuracy. They analyse a linear transshipment grid model with no time-linking constraints and conclude that complexity can be reduced by applying unit clustering followed by temporal and spatial aggregation without substantial losses in accuracy.

3.2. Temporal resolution in energy system models

The integration of multiple temporal resolutions in energy system models is as challenging as integrating multiple spatial resolutions.

The granularity of the multiple temporal scales depends on the technological characteristics of the energy system and the time horizon of the analysis. Temporal granularity is often overlooked by traditional reviews. As for spatial resolution, a high temporal resolution over a considerable time frame often punishes performances. This leads the modellers to a trade-off challenge.

Several models have an hourly resolution. ENERTILE and ReMOD model every hour of each analysed year [36,76]. METIS [80] contains different modules with different time steps, one for electricity and one for natural gas. Dispa-Set Kavvadias et al. [34] uses as its standard case single hourly time steps. The model is solved using a rolling horizon approach. EnergyPLAN [79] is a modelling framework designed for regional/national integration of intermittent renewables and conducts analysis based on hour-by-hour steps. H2RES [79] models the integration of renewable into a stand-alone energy system. It balances the renewables on an hourly basis over a user-defined time period. Using *representative periods* to integrate different modelling elements with different temporal resolutions is a common approach to temporal resolution handling in energy systems modelling, e.g. Loulou and Lehtila [95]. Merrick [74] investigates how the additional uncertainty from renewable generation increases the number of time periods needed to represent the variation. A visual representation of this approach is displayed in the upper part of Fig. 4. Different approaches may also be used in combination, and Glanzer and Pflug [96] for example classify models in two types: multiperiod models and multistage models. Babrowski et al. [58] use the PERSEUS-NET-ESS model to analyse the future electricity storage systems by first using a rolling horizon approach and then using representative daily timeslots. EMPIRE [66,67] is a capacity expansion modelling framework with a medium to long term time horizon. It considers five year time steps instead of yearly time steps for investments and also accounts for short term stochastic behaviour, as shown in the lower part of Fig. 4. In this case the Multi Horizon approach considers different types of decision in different time resolutions, whereas a Single Horizon approach would collapse every decision into a single time resolution, greatly increasing the size of the problem. Also in this case, representative time slots are used in place of using 8760 h per year. The approach of representative periods is also adopted by Li and Pye [71] for the UK-TIMES. They use 16 representative time-slots to model a year, four for the seasons and four for different parts of the day. A similar approach is used in both TIMES-Oslo and TIMES-NORWAY [78]. The JRC-EU-TIMES model [93] uses representative time steps to keep computational requirements at bay. Each year is modelled as 12 time slices, representing an average day, average night and peak demand, for each of the seasons. Time-slices are also used by the HIT modelling framework [82], which minimizes costs for electricity and heat supply within a specified area for a time-frame up to 2050 and by ESME [27], which models the major energy flows in the UK for a given demand over a short or long-term time frame. Finally, the Balmorel modelling framework [33] analyses the power and CHP sectors in the Baltic Sea Region and provides the possibility to divide each year that is to be analysed in either two, four or twelve seasonal parts and to further divide these parts into two, four or 24 time-slots. This offers the possibility to have a maximum temporal resolution of one hour for one representative day a month.

3.3. Data and resolution

Data management represents an important challenge for energy system modelling because data needs to be sampled from different sources and with different resolutions. As a mention, demand data is often available as aggregate numbers based on publicly available census data as in Druckman and Jackson [97]. Often, some form of aggregation technique is used to achieve computational tractability as proposed by Pfenninger [98] and Merrick [74].

Data aggregation is one of the main techniques employed to restore tractability. The aggregation approaches differ depending on the

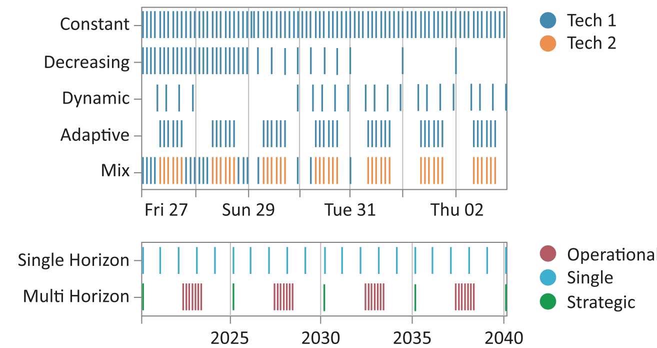

Fig. 4. Examples of different time resolutions and combinations thereof. Mix illustrates a combination of Decreasing time resolution over time for Technology 1 with Adaptive resolution for Technology 2. The lower panel illustrates a combination of Strategic time periods (5 years steps) combined with representative Operational periods, to be contrasted with a Single resolution over the full-time horizon.

characteristics of the data. Pfenninger [98] reviews methods to reduce time resolution and consider the use of three possible techniques – Resampling, Clustering and Heuristics – with the choice depending on the application.

Resampling amounts to establish representative values such as time periods in the time domain and model regions in the spatial domain. This is done when data displays a high resolution level. Clustering aims at reducing the number of data points by aggregating the initial ones; one of the most utilized clustering methods is the *k-means*, a technique that seeks to group a set of data points into k internally homogeneous clusters. Several studies suggest the use of k-means to describe highly dense data such as buildings or wind generators [86,87]. Various enhancements have been proposed for the *k-means* methods, such as the *p-max regions* [86], which allows at the same time to seek contiguous and homogeneous clusters. Siala and Mahfouz [86] use *p-max regions* to cluster wind and PV generation using a measure based on variability in wind potential, PV potential or load density as a threshold, and thereby seeking homogeneity in one of those properties. Another method, the *G-statistic method* provides means to identify hot-spots, which in our context might be a region that is statistically significantly different from the overall covered area for a given property. Rauner et al. [85] use this method for German power supply and demand. For some specific applications, it is advised to use tailor-made techniques, such as the one, based on Integer Programming, used by Unternährer et al. [87] to select clusters of buildings with heat demand while taking into account the heating resource availability. A substantial amount of research has addressed the problem of improving the quality of the approximations. These methods can be roughly classified as *hierarchical statistical methods* and *sampling techniques*. The former attempt to exploit hierarchical structures to better estimate variation between and within subgroups. They can be used when the data is structurally related. Some relevant methods are Bayesian models, e.g. Wikle et al. [99], machine learning (ML) Baño-Medina et al. [100] and multilevel or mixed models, see e.g. Sharimakin et al. [101] for application in energy demand. The latter aim at capturing the multivariate dependencies of the data, while still maintaining computational tractability. Seljom and Tomasgard [102] propose a structured sampling regime where the statistical properties are evaluated to make sure the samples capture typical time periods. This work is extended by Kaut [103].

3.4. Modelling

Apart from the handling of data, various modelling techniques have been devised to resolve the coexistence of multiple scales in time and space within the same modelling framework. As a mention, *hybrid spatial division* considers different spatial characteristics and applies to each of them tailored constraints. As pointed out by Jalil-Vega and Hawkes [90], demand can be disaggregated into urban or rural with different constraints on which technologies can serve the demand, while [93] simulating different resolutions of wind and solar resources on the supply side. Such approaches have the strength of allowing a representation of the different parts of the energy system without largely increasing the model size.

The modelling complexities introduced with the usage of different time scales are often handled by using *rolling horizon* approaches, where one analyses one subset of the full-time horizon at a time. By moving the set of time periods forward by a number of time steps, typically with some overlap between iterations, consistency between results is ensured. Marquant et al. [104] provide an example of rolling horizon methodology applied to energy hub analyses. Other methods to integrate long and short time scales is proposed by Parpas and Webster [105] (*singular perturbation theory*) and Glanzer and Pflug [96] (*multi-scale (stochastic) modelling*), but these techniques do not seem to be widely applied for energy system models. A rather important aspect of addressing multi-scale modelling in time is the inclusion or use of *extreme events* as suggested and analysed by Kaut et al. [106] and Merrick [74]. *Adaptive time resolution* is an alternative to relying on fixed and/or heuristic techniques for reducing the resolution, where the time resolution is chosen to best represent the need for detail. Vom Stein et al. [107] use an optimization model to determine the time resolution that best fit a predetermined criterion, while Bonami et al. [108] and Baño-Medina et al. [100] use machine learning, in order to select between alternative modelling choices. Pulsipher et al. [109] present a new modelling abstraction framework based on automatic discretization of infinite-dimensional problems (such as time and space) with an example application to event-constrained optimal power flow. An interesting approach to combine models with different representations of both the time and space scale is *model linking*, which is based on the mutual exchange of information between models in order to improve inter-model coherency. Linking energy system models with macroeconomic general equilibrium models is quite an established exercise, early examples are the works by Helgesen and Tomasgard [110] and Helgesen et al. [111], while a more recent example is the work proposed in Korkmaz et al. [112]. The model families have gradually expanded to include, among others, models with different temporal or spatial scales. For example, Verburg et al. [113] analyse land-use change with a multi-model framework ranging spatially from global to local by linking the computational generalized equilibrium model GTAP and the integrated assessment model IMAGE. Similar approaches have been used, albeit to a more limited extent, also within energy systems modelling. Some of these approaches include disaggregation, as is the case in the linking of the integrated assessment model GCAM and the power system modelling framework EMPIRE [67,114]. Haller et al. [115] discuss the need to supplement the traditional dichotomy between long term and short term models with models that integrate both aspects, and point to a few papers, e.g. Möst and Fichtner [116] which soft-link use of investment and dispatch models. Mancarella et al. [14] point at soft-linking as a possible method to coordinate different time resolution within the same model. A promising modelling approach to facilitate linking and decomposition in time and space as well as between different technologies is demonstrated by Jalving et al. [117,118], while an application to integrate planning and scheduling can be found in [119].

Closely related to the concept of linking models is the approach of decomposition. In this case, the main problem is split up into several smaller sub-problems which are more tractable than the full problem. For a recent example putting several of the techniques discussed above together, consider Lara et al. [120]. Finally, one broadly used technique, drawn from process systems engineering is that of *approximate modelling*, exemplified in Biegler et al. [121] and Tso et al. [122]. In each step, the model representation is extended with a *reduced model* approximating the resolution of the previous model. While the original detailed model typically has non-convexities and complex differential and partial differential equations, the reduced model uses large-scale sets of algebraic equations. The inherent trade-off between accuracy and tractability pointed out by Vom Stein et al. [107] can be gradually improved as the modelling techniques are refined. As an example, Kazda and Li [123] follow the method developed by Toriello and Vielma [124] to apply mixed-integer linear programming (MILP) following to determine the most accurate approximation of the nonlinear relationships for natural gas transport.

In energy systems modelling, there is an inherent tension between high fidelity and computational tractability and data quality, and trade-offs need to be made in order to resolve this. Several new approaches to abstraction, linking and decomposition, as well as data-driven modelling and discretization have the potential to improve these trade-offs. These new approaches also increase modelling complexity, however, and work remains to make them simple and robust to be applied at scale.

3.5. Systems with high penetration of renewable sources

The modelling of energy systems with high penetration of variable renewable sources, as well as net-zero or island energy systems are all challenges continuously mentioned in the agendas of energy system modellers nowadays. Variable renewable energy requires advanced modelling to capture unique features. Temporal resolution and planning horizons in particular are among the main challenges that are frequently addressed in literature with regard to the integration of renewable energy within energy systems models. The importance of temporal resolution in modelling deep decarbonization of the electric power sector is discussed in [125]. The study indicates that higher temporal resolution is increasingly important for both technical and economic analyses. A review of optimization models for power system planning with increasing variable renewable energy is proposed in [126] where the authors discuss strategies and requirements for resolution and planning horizon that are necessary to match constraints and time steps in optimization models. A review of models for integrating renewable energy in generation expansion planning is proposed in [127]. Models are classified into three categories, (optimization, general/partial equilibrium, and alternative models), and their properties, advantages, and disadvantages are compared. A more specific review of modelling approaches focused on power-to-heat for renewable energy integration is proposed in [128] where the authors propose a classification of existing models based on temporal scope, as well as geographical coverage, and included technologies. A classification is proposed that categorizes the most relevant models according to the general method, the type of program, model name, time resolution, endogenous investments, and whether they provide explicit formulations for power-to-heat and heat storage equations. From a geographical point of view many applications focus on northern and western Europe, while in terms of time horizon, most of the studies have a long-term time horizon, often the years 2030 and 2050. Even though there is a rich literature in terms of models tackling high penetration of renewable energy, the number of studies that derive the electrical energy storage capacity for Europe with an adequate spatial resolution is limited. To fill this gap authors in [129] propose and apply the linear, cost-minimizing optimization modelling framework REMix (Renewable Energy Mix) to tackle the dependency of the spatial distribution of storage with the regionally predominant renewable technology. A survey of modelling approaches for variable renewable energy and storage in long-term electric sector models is proposed in [130]. An example is discussed showing that models with lower temporal resolution can dampen variability, which can cause an underestimation of both variable renewable energy technologies and the role of energy storage.

4. Uncertainty

The inclusion of IRES is not only challenging the modelling of the temporal and spatial dimensions. A further complication of the new generation of energy system models is the inherent uncertainty that needs to be taken into account when considering IRES, alongside other aspects. Long-term energy system models usually consider a time horizon of 20 to 50 years and therefore rely on long-term forecasts for important parameters. New modelling approaches can no longer rely on a deterministic representation of the future. There is broad agreement that long term decision making for energy systems is subject to *deep uncertainty* [131], i.e. there is limited knowledge on the key driving forces that will shape the future, the probability distributions for key parameters and the political desirability of certain outcomes. As for the temporal and spatial aspects, handling of data and scenario generation is of primary importance. Several authors analyse available retrospectives on long term energy models [132], concluding that forecasting models tend to fail to account for pivotal events [133–135]. The most difficult parameters to estimate remain, to date, the price fluctuations of oil and gas [136,137]. Despite this unreliability of long term forecast, Goel and Grossmann [138] note that only a few approaches account for this aspect. The problem of quantification of uncertainty has been tackled by various approaches, spanning from the usage of well known continuous probability distributions [132, 139] to the definition of discrete scenarios or ranges [83,102,140]; a rather comprehensive overview of this strand of research can be found in [132], which also introduces a methodology for the characterization of uncertainty. The methodology is based on the preliminary definition of five criteria that can be followed to understand which parameters to be modelled as uncertain and which ones need to be kept deterministic. These criteria are constructed to answer a set of sequential questions related to the necessity of modelling a parameter as uncertain and whether it is possible to quantify its randomness, as well as which methods could be used to proceed with the quantification.

4.1. Methodologies to tackle uncertainty

The problem of including uncertainty in energy system modelling is approached utilizing different methodologies. Yue et al. [141] identify four prevailing techniques that address uncertainty in this class of models: *Monte Carlo analysis* (MCA), *stochastic programming* (SP), *robust optimization* (RO) and *modelling to generate alternatives* (MGA). As [141] points out, only a fraction[1] of the studies on energy system modelling adopt some approach to address uncertainty, while the majority of the analyses employ simple sensitivity analysis or alternative scenarios to evaluate the effects of uncertainties. Scenario analysis has recently started assuming a significant role in providing policy insights by exploring small groups of what-if narrative based scenarios as methods for analysing robust policies in presence of long-term uncertainty [142–144]. This approach has anyway been largely criticized as it fails to grasp the complexity of a problem with inherent uncertainty and to anticipate the real-world developments in energy systems [145,146]. A limited set of storylines underestimates the range of possible outcomes and produces a bias towards the described scenarios, which will appear more plausible than unexplored ones [147].

Monte Carlo analysis represents a popular approach to tackle uncertainty among the energy system studies. The principle of MCA is to simultaneously perturb multiple uncertain parameters and statistically evaluate the results provided by the analysis under each "roll" of the uncertain parameters. For examples of analyses based on different methodologies see e.g. Alzbutas and Norvaisa [148], Pye et al. [149], Yue et al. [150], Lehtveer and Hedenus [151], De Feber et al. [152], Hedenus et al. [153]. MCA for energy system modelling was first introduced in Seebregts et al. [154], while its large scale application was developed for the MARKAL modelling framework in [152]. Nowadays, several applications of MCA focused on energy transition and decarbonization can be retrieved in the literature [148,151,153,155]. Applying MCA requires hundreds of runs and typical energy system models entail thousands of variables, which makes this technique quite impractical for this class of problems. These limitations are often overcome by using sampling techniques to reduce the number of runs necessary to perform a satisfactory analysis [156,157], as demonstrated in [158].

Stochastic programming is the most used technique to tackle uncertainty in energy system models. The idea underlying stochastic programming is to obtain a solution that strikes a balance between immediate optimality and the possibility to adopt adjustments without incurring in large penalties. SP has been applied to extend both MARKAL and MESSAGE modelling frameworks [159,160] and later used to enhance the TIMES modelling framework [95] mainly to account for uncertain capacity shortages [161], the impacts of demand and fuel prices development in selected sectors [162,163], the impact of different fossil fuels [164] and the potential for GHG reduction [159, 165–167]. Uncertainty has also been included in the TIAM modelling framework using a stochastic programming approach to evaluate the impact of climate change on the economic assessment of long-term energy policies [164,168], to assess the role of CCS in climate mitigation [169] and to analyse the climate stabilization strategies and the effect of climate sensitivity uncertainties in the long-run [170, 171]. [102] use SP to integrate short term uncertain behaviour of IRES in a long term energy system planning model. Dreier and Howells [172] propose and test the modification of the OSeMOSYS modelling framework into a stochastic modelling framework by use of Monte Carlo analysis. The problem of integrating IRES in long term energy models has been also tackled by [66], which consider uncertainty introducing a so-called multi-horizon scenario tree approach. The methods decouple strategical and operational uncertainty by assuming that operational information does not affect subsequent strategic decisions. The method reduces substantially the computational burden featured in models based on a multistage representation. Quantitative metrics such as the expected value of perfect information (EVPI) or the value of the stochastic solution (VSS) are sometimes used to assess the importance of flexibility in providing stronger hedging options against uncertainty. [167] use EVPI to evaluate the costs of uncertainties in fossil fuel prices. VSS is used in [163] to quantify the costs of ignoring uncertainty in GHG reduction policy. This methodology is affected by issues related to the often high computational burden. The scenario structure of this approach leads to an exponential increase of memory requirements with the number of considered scenarios. These problems can be partially overcome by utilizing decomposition techniques and parallel computing.

When the computational burden might be too high to adopt SP, *robust optimization* represents a computationally cheaper alternative. This paradigm considers uncertain parameters equipped with geometrically based ranges of variation but in general, models are solved using a conservative approach. The first to propose the utilization of this framework in the analysis of long-term energy system planning was [173], with a focus on inter-regional pollutant transfer rates. Robust optimization was then used by [174,175] to analyse the impacts of the transport sector and fuel costs on the energy system. A large scale application of robust optimization in the analysis of energy security at a European scale was provided by [176], using the TIAM modelling framework. Robust optimization offers a computationally treatable alternative to more heavy techniques such as SP. However it is mostly targeted to the analysis of the worst-case scenario, and it is bound to only use a limited number of uncertainty sets, whereas SP and MCA both can use any possible distribution for the random parameters.

[1] Around 34% of the energy system optimization models considered by the authors address uncertainty in their analyses.

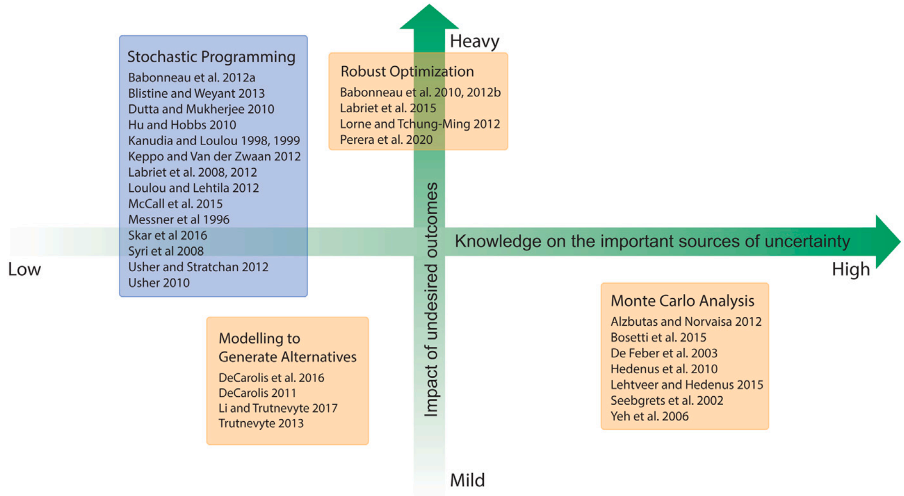

Fig. 5. Guidelines in the selection of methodology to tackle uncertainty in energy system modelling. The orange boxes depict methodologies fit to model cases with large numbers of random parameters.

The fourth modelling technique, *modelling to generate alternatives* is used to analyse political and decisional uncertainty [150,177]. As described in the beginning of the section, energy system models are subject to deep uncertainty; it is simply impossible to model the reality as such in a perfect way. Therefore, solutions lying in a neighbourhood of the optimal solution might, in reality, be more desirable than the optimal solution itself. MGA is based on using a modified model formulation to search the near-optimal solution space for alternative solutions. These solutions are supposed to perform quite similarly with respect to the known modelling features, yet they should behave very differently with respect to any unknown, unmodelled and/or unquantified aspect of the problem. This method was first introduced in the analysis of energy system models by [178], which later applied the same method to the TEMOA modelling framework to analyse alternative future developments of the US electric and light duty transport sector [179]. In [180,181], the EXPANSE (Exploration of Patterns in Near-optimal energy ScEnarios) methodology is used to evaluate the profitability of renewable energy sources to cover heat demand and for the analysis of possible pathways for the UK power sector. MGA is not to be considered a methodology to tackle uncertainty in a classical sense, as it is used for analysing structural and political uncertainties rather than parametric uncertainties.

Fig. 5 displays a visual representation for the trends related to the selection of a modelling approach to tackle uncertainty in energy system modelling. The light red squares depict methodologies fit to model cases with large numbers of random parameters, while the light blue square considers methodology which might have issues when considering a high number of random parameters. As those models tend to be large-scale the number of uncertain parameters that need to be modelled highly influences the approach that is usually selected. In fact, Stochastic Programming is a good choice only when the additional complexity brought into the modelling framework is limited. In other words, the approach is suitable only with a limited number of uncertain parameters. In cases with a large number of uncertain parameters, the choice of modelling framework is based on the knowledge of the drivers that exert the largest impact on the solution. If we do not know much about the possible impact that the random parameters might exert on the solution and therefore we do not have a predefined policy to test, the possible approaches could be Robust Optimization or Modelling to Generate Alternatives, where the first approach is more suitable if there is particular need to hedge for undesired outcomes. In case we know which parameters are the most impactful and we already have a policy that we want to test, then Monte Carlo Analysis is a good candidate.

When dealing with uncertainty, a special emphasis should be put on the dramatic climatic changes that are happening, raising interest in the ability of models to deal with extreme events. From this point of view, there has been a call for models to deal better with different types of extreme events, as these are likely to become more frequent. A review discussing the impact of climate change on the energy systems was proposed in [182] where the authors examine the ways in which the impact of climate change has been represented within models of the electricity or energy system. Another review of current practices in modelling extreme events for resilience evaluation and enhancement of power systems is proposed in [183]. A review on how energy systems models and scenarios have been used to capture disruption and discontinuity is proposed in [184]. The main finding is that the most frequently used methods are qualitative, exploratory foresight scenarios or agent-based models. Several recent works in literature have made a significant effort to tackle the challenges of extreme events within models of energy systems. A framework to manage the operation of hybrid renewable energy systems under extreme events and disasters is proposed in [185]. Here optimal systems configurations are generated for different extreme events, with key criteria of minimizing the number of blackouts. A statistical approach to identify extreme events for multi-regional energy system models is presented in [186]. The authors show that extreme events are extremely important to be included in the input dataset, to improve the output accuracy of the model. A modelling framework for extreme events with a focus on power grids is developed in [187]. The authors focus on the operation of multi-time scale power systems to reproduce cascading outages and calculate resilience in extreme events. A stochastic-robust optimization method to consider extreme weather events induced by climate change is developed and tested in [188], by considering 13 climate change scenarios. Other recent studies discuss scenario generation and input dataset definition to better catch the representation of the extreme events. An example is given in [189] where the aim is to identify extreme events in meteorological time series relevant for renewable energies. This approach would lead to an improvement of both weather and climate predictions and therefore a better quality dataset for energy systems models.

While the inclusion of uncertainty allows for a better representation of variables and parameters (such as demand, renewable production and electricity prices) and therefore a more consistent decision making process, it also affects the computational complexity of the models. Therefore additional approaches such as cluster computing, parallel computing, decomposition techniques, heuristics algorithms, and machine learning have to be investigated on top of the models to tackle such challenges.

5. Energy behaviour and energy transitions

Even the most comprehensive of the models could fail to predict the future developments of the energy system. A very important, and often neglected or oversimplified, aspect of both decision making and the resulting technical and economic impacts are energy behaviour and the dynamics of the energy transition. The modelling of social and human aspects of energy transition and energy use is a challenge because of various reasons. First and foremost, long term planning literature often assumes consumers and producers to be economically rational actors that maximize their utility and profits respectively. The issue that this generates has been known by economists for decades and was summarized by Sterman [190], who states that "people do not optimize or act as if they optimize, ...(and) even if they had the computational power necessary, they lack the information needed to optimize". This point on real decision-makers – whose decisions rest on routines and reduction of complexity more than complex optimizations – is met with a more recent concern when the energy transition is at stake. McDowall [191] discusses the difficulties of modelling such an environment. The reason for these difficulties can be mainly traced to the fact that energy transitions involve a change in the rules, technologies, and organizational structures of the energy system and the actors that are involved, but many energy systems models assume the system to be rather static [192]. Past studies confirm that many modelled energy forecasts such as those used in the UK have been shown to be consistently outside of the scope of real-world events [193].

This section presents a set of new models that rise to the challenge of representing consumer behaviour and energy systems in transition in greater depth. Most parts of these models consider a combination of quantitative and qualitative data and outputs [191]. Namely, a critique of existing energy systems models and a focus on human and behavioural issues and energy transition does not mean abandoning quantification as a research objective, quite the contrary: the objective is to bridge the gap between the convenient but often too simplistic assumptions utilized in standard energy models and produce a leap forward in the representation of energy transitions, society, the role of politics and policy, and everyday behaviour.

A great diversity of modelling techniques and approaches are used for energy behaviours and transitions, drawing on different academic disciplines: from statistics and economics to sociology, computer science, mathematics, psychology, and marketing [194]. Following [195], a model is a representation that formalizes, simplifies, and stylizes a part of reality. We consider three areas that models of energy transition and energy behaviour should touch upon in order to perform a comprehensive analysis of the energy transition. For each of these areas, we will consider the models that nowadays are providing a contribution to the analysis. These areas reflect challenges that these models are subject to in terms of understanding the energy transition and its impacts in everyday life and for various stakeholders related to energy systems.

5.1. Actors, agents, and practices

Modelling of demand is one of the main contributions that behavioural models can provide to the analysis of energy transition patterns. The premise for the usage of these models is that behavioural patterns linked to energy usage are affected by a great number of factors, from lifestyle choices to household economics [196]. This has called for an "integrated approach" to model behavioural patterns which has been met by several different kinds of models, many of them drawing from complex systems thinking and advancing the capabilities of conventional modelling tools [197]. 'Non-optimal' energy-related behaviour is modelled by [198]. This model produces important outputs – including probability densities of carbon emissions and technology portfolios (in percentages of different technologies) – to carbon emissions strategies that correspond with findings from behavioural economics and political science. Fragnière et al. [199] develop a similar new method that takes "real consumer behavior" into account in planning models for future energy systems. The modelling of 'non-optimal' behaviour has been most developed under the auspices of agent-based modelling (ABM) [197]. ABMs are computational models that simulate the interactions and actions of what are termed as "agents". These simulated agents – which can be individuals, households, or broader organizations – can be assumed to be perfectly rational, but do not have to be. Rather, an ABM creates the rules that these agents follow. ABMs are not only used in forecasting electricity prices in electricity markets, but also for simulating quantitative trends in consumer behaviour: for example, representing energy demand and its complexity, such as the impacts of social interactions and space more appropriately than conventional energy models and reflecting on social theories [200]. Higginson et al. [201] expand this premise on actors and decision-making and conduct an experiment to construct energy models that would acknowledge new social science theories of everyday practices in households, with a focus on energy demand modelling.

5.2. Energy sustainability transitions

Even though addressing the importance of accounting for behavioural effects in energy system modelling, many of the tools available to integrate such dimension are focused on real-time interactions rather than transitions that happen over several decades. They tend to take the transition as given and ignore its dynamics [192]. Therefore these models are currently more suitable for being utilized through a model linking approach, similar to how it is often done to integrate different time and space scales, as explained in Section 3. In this respect, Holtz et al. [195] argue for the creation of a research community that would adopt energy models and use them toward an enhanced understanding of energy transitions, including in support of active transitions management. Parts of this research community have affirmed the use of formalized models to understand energy transition, especially in order to develop a structured view into what are essentially highly complex and multi-dimensional transitions [202]. Moreover, in order to avoid oversimplification, [191,203] claim that there should be more room for interdisciplinary dialogue between qualitative and quantitative approaches, where quantitative models and qualitative studies can clearly complement each other even if they are not tightly coupled. Li et al. [192] bring many of these themes together in their review, where they detect an emerging paradigm of energy models that combine quantitative approaches with conceptual insights arising from energy transitions, named socio-technical energy transition (STET) models. They outline three requirements to qualify as such a model: (1) techno-economic detail in the model, (2) heterogeneity of actors that influence the transitions in the model, (3) key transition dynamics included by the model, such as 'radical innovations' that disrupt incumbent regimes, or landscape pressures that happen over several decades. This important study confirms that modelling of social aspects of energy cannot be achieved by a single approach but is likely to be a combination of models with different strengths and weaknesses.

Finally, the still ongoing COVID-19 pandemic has had visible effects on energy demand, prices, public policy and the energy sector globally (see e.g. [204,205]), though the long-term impacts on energy transition remain to be seen. Here, we merely note that relevant studies are emerging, and some modelled scenarios (e.g. [206]) have suggested plausible effects to energy demand reduction toward 2030. Overall, however, we cannot address the long-term implications of the pandemic on the energy transition in this review, but our paper suggests that several integrated models are beneficial to address the complex cross-sectoral impacts as they unfold.

5.3. Energy policy and politics

The final, and particularly important element of energy transitions that needs to be taken into account in models is the role of energy policy and politics. According to the literature, most energy transitions must be actively managed by long-term thinking among governments and by using practical policy processes [207]. There are at least two ways to respond to this importance of policy and politics in modelling: loose and tight coupling of models and policy. The first approach means acknowledging that policy-problems should drive modelling analyses, including what models are selected to do these tasks [208,209]. For example, Strachan et al. [210] devise an approach to improve this interface which relies on several elements: including coupling models with policy cycles and funding cycles, development of new modelling platforms, and various forms of increased accountability such as external review of models by wider stakeholders and quality assurance. The second approach means an attempt to model the policy process itself. Li and Strachan [211] used BLUE (The Behaviour, Lifestyles and Uncertainty Energy model) to focus on government-led and societally-led energy transitions. Their model produces profiles of carbon taxation and statistical distributions of energy-using social groups and accounts for societal and political drivers of energy transitions and their heterogeneity and co-evolution. Fortes et al. [212] link socio-economic storylines of energy futures with a planning model (TIMES). By this integrated approach, they recognize several limitations: quantitative models provide cost-effective solutions that may not match the expectations of different stakeholders and impacts of long-term policy, whereas socio-economic storylines have too little consideration for complex variables and interdependencies over the long period. Anable et al. [213] also model transport energy demand by combining a qualitative scenario exercise with whole quantitative systems models. By reviewing planning tools for renewable energy systems, Cuesta et al. [214] argue that current tools largely lack integration of socio-economic objectives such as job creation or increasing acceptance into the optimization. This shows further potentials of meeting the expectations of various stakeholders in an integrated modelling process.

As these studies demonstrate, there is no single approach to integrate models with the impact of energy politics and policy choices. The most appropriate approach could benefit from linking different approaches [191]. An indication of the main approaches is given in Fig. 6, showing complementarities and differences between the three key areas that were reviewed.

The clearest advantage of taking a wider perspective on society to modelling is contained in the assumption of these models reviewed: the models developed should be more sensitive to the dynamics of everyday behaviour, the effects of the energy transition, and the manifold impacts of political and policy decisions. That said, as this section has shown, modelling these aspects of society is far from a paradigmatic practice, and a scholar on this area still has to navigate between multiple approaches and disciplinary orientations. The disadvantage of these modelling approaches thus may be the same as the challenges of interdisciplinary working in general: that is to say, the active need to coordinate between academic disciplines and demanding questions on which aspects of social science data can ever by 'translated' to modelling inputs and outputs. Scholars on this area should be encouraged to keep their research practice reflective by attuning to different kinds of research knowledge and the limits of its integration in designing models.

6. Conclusions

Despite a large body of ongoing research within the energy systems modelling field, there are many aspects that are yet to be covered or that have been only marginally considered. This paper has addressed four main challenges, which the authors believe will be key drivers for the future development of energy systems models. The trends, gaps and suggested research directions for each of them, can be summarized as follows.

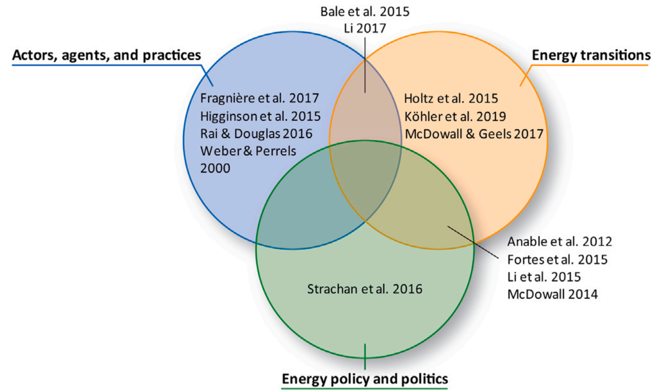

Fig. 6. Three main approaches in modelling energy behaviour and energy transitions.

Multi-energy systems

Modelling cross-sector interdependencies among energy carriers will be central to ensure efficient integration of large shares of variable RES with minimal curtailments. Most importantly, the coupling of electricity and heat should be an inherent part of the analyses of any energy transition pathway. In this realm, both short-term operations and long-term modelling considerations on infrastructure investments are crucial to catalyzing synergies and coupling points in multi-energy systems. In addition, other concrete modelling frontiers are the integration of key emerging decarbonization technologies such as H_2 value chains and CCS infrastructure needs, and stronger representation of demand sectors and demand-side management. Regarding the latter, the focus on electric vehicles and household appliances is, for the time being, higher than for industrial demand-side management in key energy system models. Overall, there is a lack of demand-side management applied to multi-carrier energy system models and the inclusion of prosumers (e.g. flexible local markets) is explored only in a limited manner.

Time and spatial resolution

Time and spatial resolution are prominent aspects of modelling new generation energy systems, featuring local generation and large renewable sources integration. The need of modelling multiple time resolutions is generated by the interplay between long term expansion planning and the short term behaviour of renewable sources. A coarse representation of the behaviour of these sources might over- or underestimate their contribution to the overall system, and therefore lead to a biased evaluation of the necessary capacity investments.

Many attempts to combine fine resolution with long time horizons and large spatial coverage have been adopted, with the use of representative time periods and geographical aggregation being the dominating approaches. New approaches are tested, such as data-driven methods, adaptive resolution methods, and structured sampling methods.

Future research should focus on more transparent choices and validation of approximation and data processing in order to support the process of adding more advanced methods to the "standard tools". Moreover, there is ongoing research to establish general frameworks for multi-scale modelling that should be considered in several dimensions, time, space, technology and energy carrier.

Uncertainty

The effects of the integration of intermittent renewable energy sources in the energy system are not limited to the need to account for multiple temporal and spatial scales, as it also introduces uncertainty into the short term behaviour of the system, whereas long term electricity demand and fuel prices development, as well as political decisions about climate control measures, introduce stochasticity in the long run. Energy system models need to account for this uncertainty in order to avoid adopting biased policies. Different approaches have been used in literature, which differentiate on the type of output that they provide and the level of computational complexity.

However, uncertainty is often a neglected aspect of long term energy system models, which only focus on few parameters in every study, neglecting cumulated effects of all the possible random parameters at once. There is a lack of studies modelling uncertainties related to emerging technologies, as well as the projected cost-effectiveness of technologies that are currently not profitable.

Future research should extend the consideration of uncertainty in energy system models, to incorporate possible unilateral policy changes by other actors.

Modelling energy behaviour and energy transitions

The dynamics of energy transitions and activities by various actors – including policy makers, companies, and consumers – are often overlooked or simplified in modelling energy systems. In recent research, a set of new models have risen to face the challenge of representing transitions of energy systems and societies towards a low carbon future. These models span from detailed consumer decisions and interactions to long-term transition dynamics. Some models even integrate energy policy requirements and political decisions as part of their design.

Developing such models especially those that represent society, governments, and their relationships, is a challenging issue. While appropriate modelling methodologies are part of this problem, this development needs to be informed by advancements in political and social theory, so that the models do not end up reifying outdated or overly simplistic conceptions about governance.

The modelling of energy consumer behaviour is also clearly one, if not the only, aspect of future research. Here, it can be expected that more complex theories about this behaviour – such as social practices and collective rather than individual decision making – will be attempted to be integrated into energy modelling. When looking further into the future, the modelling of long-term uncertainty will be an integral element of the modelling of societal transitions. In doing so, the integration of qualitative scenarios to challenge formal energy models has seen considerable development, but will undertake more in terms of appropriate methods and integration of different knowledge bases (e.g. qualitative vs. quantitative data).

In addition to the challenges outlined above, it is worth mentioning that collaborations between modellers, empirical researchers, policy makers, and different academic disciplines need to be developed to advance model building and the maturation of theory. While some models will be built anew, the urgency of energy transition means that the use and integration of existing models should be supported in this field. The validation of the models in this field is work-in-progress, and modellers should be wary of possible over-simplifications of complex transition processes and social practices of energy use and policies as part of their models.

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.

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