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A systematic approach to analyze integrated energy system modeling tools: A review of national models

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Abstract

We reviewed the literature focusing on nineteen integrated Energy System Models (ESMs) to: (i) identify the capabilities and shortcomings of current ESMs to analyze adequately the transition towards a low-carbon energy system; (ii) assess the performance of the selected models by means of the derived criteria, and (iii) discuss some potential solutions to address the ESM gaps. This paper delivers three main outcomes. First, we identify key criteria for analyzing current ESMs and we describe seven current and future low-carbon energy system modeling challenges: the increasing need for flexibility, further electrification, emergence of new technologies, technological learning and efficiency improvements, decentralization, macroeconomic interactions, and the role of social behavior in the energy system transition. These criteria are then translated into required modeling capabilities such as the need for hourly temporal resolution, sectoral coupling technologies (e.g., P2X), technological learning, flexibility technologies, stakeholder behavior, cross border trade, and linking with macroeconomic models. Second, a Multi-Criteria Analysis (MCA) is used as a framework to identify modeling gaps while clarifying high modeling capabilities of MARKAL, TIMES, REMix, PRIMES, and METIS. Third, to bridge major energy modeling gaps, two conceptual modeling suites are suggested, based on both optimization and simulation methodologies, in which the integrated ESM is hard-linked with a regional model and an energy market model and soft-linked with a macro-economic model.

1. Introduction

The long-term energy strategy of the EU is aimed at a 80–95% reduction of Greenhouse Gas (GHG) emissions by 2050, relative to 1990. Reaching this goal requires a number of key actions to make a transition from a conventional energy system to a low-carbon energy system [1]. As a result, low-carbon Energy System Models (ESMs) have been developed to guide decision-makers on taking long-term robust policy decisions towards energy system transition. However, every ESM has been developed to answer specific policy questions, due to the complexity of the energy system and limited computational power. As a result, each model comes with specific capabilities and shortcomings.

A large growing body of the literature has listed and classified ESMs with different aims and scopes. Connolly et al. provided a comprehensive overview of suitable ESMs addressing issues related to renewable energy integration [2]. Similarly, Bhattacharyya et al. compared energy models to identify their suitability for developing countries [3]. Aiming to find the prevalent modeling approaches for the U.K., Hall et al. classified and compared ESMs based on their structure, technological detail, and mathematical approach [4]. To find trends in energy system modeling, Lopion et al. reviewed ESMs in a temporal manner [5]. Some reviews have emphasized the role of policy strategies and the corresponding modeling challenges. By grouping energy models into four categories, Pfenninger et al. examined the policy challenges they face in each group [6]. Horschig et al. reviewed ESMs to provide a framework for identifying a suitable methodology for the evaluation of renewable energy policies [7]. While Savvidis et al. identified the gaps between low-carbon energy policy challenges and modeling capabilities with a focus on electricity market models [8], Ringkjøb et al. classified ESMs with a focus on the electricity sector [9]. Lastly, Li et al. reviewed socio-technical models emphasizing societal dynamics [10].

The increasing share of Variable Renewable Energy Sources (VRES) has caused the low-carbon energy system transition to face several major challenges, such as the increasing need for flexibility, further electrification, emergence of new technologies, technological learning,
integration of renewables in Europe, while assuming no national high shares of renewables, while neglecting the heat and transport sectors [14]. Brown et al. analyzed the cross-sectoral and cross-border integration of renewables in Europe, while assuming no national transmission costs, limited efficiency measures, and limited technology options [15]. Social aspects of the energy system transition are usually neglected in ESMs. To this end, some studies included actors’ behavior in the energy system from the demand perspective, for example, the thermal demand transition [16] or the efficiency of adaptation measures in households [17]. Analyzing each of the major changes in the energy system can be challenging for conventional ESMs as they need further capabilities such as fine technological detail, high temporal and spatial resolutions, and the presence of stakeholders’ behavior.

This study concentrates on the energy modeling challenges which result from the increasing share of VRES, complexity, and system integration. The transition towards a decarbonized energy system involves other policies such as the higher energy efficiency and change in energy demand, the use of nuclear power supply, and using Carbon Capture Utilization and Storage (CCUS) technologies. Due to the diversity of ESMs, two major limitations were imposed in this review. First, we focused on energy models at the national level. Therefore, the reviewed models were designed for national analysis (or they can be used for national assessments, e.g., PRIMES). Second, the models covered all energy system sectors (i.e., residential, services, agriculture, transport, and industrial sectors).

The overarching research question of this study is “What are the potential solutions to address the shortcomings of current ESMs considering current and future low-carbon energy system challenges?”. To answer this question, we first describe the current and future low-carbon energy system modeling challenges. Based on these modeling challenges, we identify the required modeling capabilities, such as the need for hourly temporal resolution, sectoral coupling technologies (i.e., P2X), technological learning, flexibility and storage technologies, human behavior, cross border trade, and linking with market and macroeconomic models. The required capabilities were then translated into assessment criteria to be used in the Multi-Criteria Analysis (MCA). Finally, potential model development solutions are discussed and a modeling suite is proposed as a model-linking solution to address the energy modeling challenges. (Fig. 1)
2. Method

Seven major low-carbon energy system modeling challenges were identified. The challenges were translated into a number of required energy system modeling capabilities and criteria.

Nineteen models were selected from other reviews ([2,4]). Primary inclusion criteria for the selected models (see Table 1) were: (1) being used at national level, and (2) covering the whole energy system (i.e., integrated energy system models). All the information from the selected models was gathered from officially published documents that may be incomplete or outdated (notably when this paper is published), as models are continuously developed. For each model, a brief description was provided in the Appendix section.

AHP multi criteria analysis was used as a transparent framework to analyze diverse ESMs from different perspectives. MCA is a methodology that evaluates complex choices (i.e., various criteria, objectives, and indicators), which has been used extensively to analyze energy transition policies [40]. The major advantage of MCA is that it provides a rational structure of complex alternatives that presents substantial elements for identifying the desired choice [41]. Although MCA may have different purposes, we were particularly interested in: first, breaking down complicated energy models into key criteria; and second, identifying the importance or relative weight of each criterion for each alternative. Models were ranked based on known criteria, but this did not mean one model was superior to others. Therefore, the intention was not to compare models but to identify modeling capabilities and gaps when used for structuring a low-carbon energy system modeling framework.

Based on the identified modeling gaps, a conceptual modeling suite was proposed to address future low-carbon energy system modeling challenges. The proposed suite included a core integrated energy system model that was hard-linked with a regional model and soft-linked with both an energy market model and a macroeconomic model.

3. Low-carbon energy system modeling challenges

Energy policies are designed to meet three key objectives, which are providing energy reliability (i.e., supply security), affordability (i.e., economics and job creation), and sustainability (i.e., environment and climate) [42]. With the aim of reviewing electricity market models, Savvidis et al. [8] clustered twelve energy policy questions as a basis to quantify the gap between models and policy questions. Based on the literature and experts’ opinions, we divided energy modeling related policy questions into four categories as follows:

Fig. 1. Proposed modeling suite approach.

Table 1

| Model | Developer / Source | Model | Developer / Source |
|-------|-------------------|-------|-------------------|
| DynEMo | UCL / [16,19] | METIS | Artefaqs / [20] |
| E4Cast | ABARE / [21] | NEMS | EIA / [22] |
| EnergyPLAN | Aalborg University / [23] | OPERA | EBN / [24] |
| ENSYS | PBL / [25] | OsMOSYS | KTH, UCL / [26] |
| ESME | ETI / [27] | POLES | Enedata / [28] |
| ETM | Quintel Intelligence / [29] | PRIMES | NNTU / [30] |
| IKARUS | Research Center Jülich / [31,32] | REMix | DLR / [33] |
| IWES | Imperial College London / [34] | SimREN | ISUS / [35] |
| LEAP | Stockholm Environmental Institute / [36] | STREAM | Ea Energy Analyses / [37] |
| MARKAL, MARKAL- MACRO, TIMES | IEA / [38,39] | | |

1. Technical questions, such as a lack of insights in higher share of intermittent renewables, role of new technologies, and further electrification of the energy system.
2. Microeconomic questions, such as a lack of insights in decentralization, human behavior, and liberalized energy markets.
3. Macroeconomic questions, such as a lack of insights on economic growth and jobs due to the energy transition.
4. A mix of the above questions, such as lack of insights on the effect of further electrification on energy markets.

Providing a solution for each policy inquiry can be a challenge for energy system modeling. These challenges can alter the choice of modeling methodology and parameters. In this section, energy modeling challenges and the corresponding modeling parameters are described.

3.1. Intermittent renewables and flexibility

Some sources of renewable energy such as wind and solar energies have an intermittent characteristic i.e., they are (highly) variable and less predictable [43]. The power generation from intermittent renewables is directly dependent on weather conditions [44]. As wind and solar power generation technologies are becoming more competitive [45], it is expected that wind and solar power generation will cover up to 30% and 20% of the EU’s electricity demand by 2030, respectively [46, 47]. Hence, a high share of intermittent renewables in the electricity generation sector is imminent.

3.1.1. Variability

Technically, the power system needs to be in balance at all temporal instances and geographical locations. Therefore, the electricity sector should be structured in a way to ensure the balancing of demand and supply. The higher share of intermittent renewables entails variability on the power system balance [48]. Solutions to deal with power balance variabilities are called flexibility options (FOs) as they provide flexibility to the power system against the variable and uncertain residual load profiles.

Traditionally, conventional power supplies and grid ancillary services were primary sources of flexibility. However, the power system needs further FOs as the share of intermittent renewables in the power generation increases while the share of conventional power supplies - i.e., notably dispatchable gas-fired power plants - decreases. Several review papers can be used as a starting point for a review on FOs ([49,50]). Lund et al. [51] listed different FOs as Demand Side Management (DSM), storage, power to X, electricity market designs, conventional supply, grid ancillary services, and infrastructure (e.g., smart grids and microgrids). Further, Sijm et al. [24] investigated FOs by suggesting three
causes of the demand for flexibility as the variability of the residual load, the uncertainty of the residual load, and the congestion of the grid. Michaelis et al. [52] divided FOs based on the residual load in three groups: downward, upward, and shifting flexibility. Due to high detail and complications regarding each FO, some studies focused mainly on one or a few technologies. To name a few examples: Blanco et al. investigated the cost-optimal share of power to methane in the EU energy transition [53]. The potential of power to heat and power to ammonia in the Dutch energy system was investigated by Hers et al. [54] and ISPT [55], respectively. Some other studies followed an integrated approach that included several FOs in different sectors; however, they made several assumptions as the computational capacity was limited (e.g., see Ref. [15]).

Flexibility options can be divided into five main groups, i.e., storage, demand response (DR), VRE curtailment, conventional generation, and cross border trade. Instead of analyzing the pros and cons of each option, we were interested in identifying key energy modeling issues regarding each flexibility option. (Fig. 2)

3.1.2. Storage

From a temporal perspective, storage FOs can be divided into daily and seasonal storage options. On the one hand, solid-state and flow batteries, such as Li-ion, Ni-Cd, NAS, ICB, VRB, and ZnBr batteries, provide high ramp rate with limited capacity, which is suitable for diurnal power storage. Modeling these batteries with diurnal temporal resolution can be different to Hourly Temporal Resolution (HTR) or hourly time-slices (i.e., grouping hours featuring similar characteristics [56]). Improvements in temporal resolution can have a significant impact on modeling results considering the high share of intermittent renewables (e.g., see Ref. [43,57,58]). On the supply side, the uncertainty regarding weather forecasts needs to be implemented in the model as weather conditions have a significant impact on intermittent renewables’ generation (e.g., see Ref. [59-61]). On the other hand, technology options, such as Pumped-Hydro Energy Storage (PHES), Thermal Energy Storage (TES), Large-Scale Hydrogen Storage (LSHS), and Compressed Air Energy Storage (CAES), provide huge capacities that makes them suitable for seasonal energy storage. Modeling seasonal storage options requires the inclusion of Chronological Order (ChO) of the temporal parameter together with a fine temporal resolution, as the chronological order of time from summer to winter (and vice versa) determines the charge/discharge of seasonal storage options.

3.1.3. Demand response

DR refers to a set of schemes to shift the demand in a certain time period (e.g., an hour) to another time period of the day, week, or month, either forward or backward [24]. Currently, electricity comprises around 22% of EU final energy consumption. Power to X (P2X) technology options can provide further DR potentials by linking energy sectors and energy carriers together through converting electricity to other forms of energy, services, or products. In its latest report, the World Energy Council suggests that P2X will be a key element for the transition to a low-carbon energy system [62]. Due to high detail and complications regarding each technology option, several studies focus mainly on one or a few options. At EU level, Blanco et al. investigated the cost-optimal share of P2G in the EU energy transition [53]. At the national level, the potential of P2Heat [54] and P2Ammonia [55] in the Dutch energy system was examined.

There is a huge potential for demand response in the built environment as it is responsible for 40% of energy consumption and 36% of CO2 emissions in the EU. While individuals can passively participate in either price-based 1 or incentive-based 2 demand response schemes [63], proactive participation of consumers can increase market efficiency and reduce price volatility [64]. As heating demand averages 80% of EU household energy consumption, the DR potential can be realized by coupling electricity and heat demands. DR in the built environment can consist of three main components including P2Heat technologies (e.g., heat pumps and electric boilers), storage (e.g., thermal tank storage and thermally activate building), and smart controllers (that consider market participation, consumer behavior, and weather forecast) [65].

As P2X technology options bridge two different energy sectors or carriers, analysis of these options requires multi-sectoral modeling, and preferably, integrated energy system modeling. Moreover, the hourly temporal resolution of the power sector should be maintained. Table 2 summarizes key modeling capabilities and concerning energy sectors and carriers for each P2X technology option.

3.1.4. VRE curtailment and conventional generation

VRE curtailment and conventional generation options have been used as FOs in the power sector. Modeling these options is relatively straightforward, as they do not involve other sectors or energy carriers. Still, the hourly temporal resolution remains the key modeling capability for these options. From the energy security perspective, modeling conventional generation may require modeling capacity mechanisms, 3 preferably in combination with cross border power trade [66].

3.1.5. Cross border trade

The EU is promoting an internal single electricity market by removing obstacles and trade barriers (see e.g., COM/2016/0864 final -2016/0380). “The objective is to ensure a functioning market with fair

![Fig. 2. Flexibility options classified by their temporal scale. Note: Dashed options are usually excluded from integrated national energy models.](image-url)
market access and a high level of consumer protection, as well as adequate levels of interconnection and generation capacity” [67]. One of the products of an internal EU electricity market is the potential to offer flexibility in the power system, as the load can be distributed among a larger group of producers and consumers. Sijm et al. identified the cross-border power trade as the largest flexibility potential for the Netherlands [68]. Similar to other flexibility options, one of the key modeling capabilities here is the hourly temporal resolution.

Table 2 summarizes the required key modeling capabilities for representing and analyzing flexibility options in ESMs. The main requirement is the inclusion of (at least) an hourly temporal resolution. Models’ capabilities can improve substantially by adding seasonal storage options, which require the inclusion of chronological order and different energy carriers. Moreover, the inclusion of cross-border trade can play an important role in the optimal portfolio of flexibility options, especially in EU countries.

3.1.6. Uncertainty
Higher shares of intermittent renewables affect the reliability of power generation and distribution as residual loads become less predictable. For instance, the prediction accuracy of a single wind turbine generation decreases from 5-7%–20% mean absolute error for the hour ahead and day-ahead forecasts, respectively [69]. The increased uncertainty of the power generation due to higher shares of VRE sources requires models to include short-term weather forecast and balancing mechanisms in their calculations.

Uncertainty analyses gain more importance for long-term ESMs as they model the energy system for several decades in an uncertain future that can get affected by parameters outside the energy system boundaries. Energy system optimization models use four main uncertainty analysis methods, which are Monte Carlo Simulation (MCS), Stochastic Programming (SP), Robust Optimization (RO), and Modeling to Generate Alternatives (MGA) [70].

3.2. Further electrification
In 2017, almost 22% of the EU final energy demand was satisfied by electricity, while heat consumption and transport accounted for the rest. Current heating and cooling production in the EU come from fossil fuel sources, as renewable energy sources have a 19.5% share of gross generation decreases from 5-7%–20% mean absolute error for the hour ahead and day-ahead forecasts, respectively [69]. The increased uncertainty of the power generation due to higher shares of VRE sources requires models to include short-term weather forecast and balancing mechanisms in their calculations.

In 2017, almost 22% of the EU final energy demand was satisfied by electricity, while heat consumption and transport accounted for the rest. Current heating and cooling production in the EU come from fossil fuel sources, as renewable energy sources have a 19.5% share of gross heating and cooling consumption. The transport sector is highly dependent on fossil fuels, with only 7.5% of final energy consumption from renewables. Therefore, decarbonization of the heat and transport sectors is getting more attention as it has a higher GHG emissions reduction potential. The EU Commission suggests electricity as an alternative fuel for urban and suburban driving in its report entitled Clean Power for Transport [71]. Further electrification of heating, cooling, and transport sectors may contribute to GHG reduction, assuming the electricity is generated from renewables rather than fossil fuels [72].

Due to the high seasonal variation of heating and cooling demand profiles (mainly in the built environment), further electrification of this sector requires huge seasonal storage capacities or other flexible supply options. Currently, there are four main high capacity seasonal storage options, which are Pumped Hydro Energy Storage (PHES), Compressed Air Energy Storage (CAES), Thermal Energy Storage (TES), and Hydrogen Energy Storage (HES). By using TES technologies, hourly heat and power demand profiles can be decoupled resulting in a higher potential for DR flexibility option [73]. TES technologies can be divided into three main groups based on their thermodynamic method of storing heat energy: sensible, latent, and chemical heat [74]. Sensible Heat Storage (SHS) technologies stock the heat by the difference in the materials’ temperature, for example by warming up water or molten salt tank. Latent Heat Storage (LHS) technologies make use of Phase-Change Materials (PCM) in a constant-temperature process to absorb or release thermal energy. Chemical Heat Storage (CHS) technologies make use of Thermo-Chemical Materials (TCM) in a reversible endothermic or exothermic (i.e., a chemical reaction in which the heat is absorbed or released, respectively) process, for example, the reversible ammonia dissociation process (i.e., $2\text{NH}_3=\text{N}_2+3\text{H}_2$). Xu et al. [75] provided an extensive review of current seasonal thermal energy storage technology options.

Further electrification of the energy system, which is expected to account for 36–39% of final EU energy consumption by 2050 [76], generates higher interdependencies between energy sectors. Single sector models, which are not able to capture sector coupling effects, may provide misleading conclusions by neglecting these interdependencies. As more sources of intermittent renewables are deployed in the energy system, the further electrification implies further volatility of the energy system that highlights the higher demand for flexibility options. Moreover, analyzing sector coupling technologies such as EVs (P2Mobility), heat pumps and electric boilers (P2Heat), and electrolyzers (P2Gas) become more important. Inclusion of sector coupling options in the ESM requires modeling of electricity, transport, and heat sectors simultaneously. Due to high variations in the electricity supply, a fine temporal resolution should also be employed in the transport and heat sectors in order to adequately address the flexibility issues of sector coupling.

3.3. New technologies, technological learning, and efficiency
Development of new technologies and technological change are key drivers of the transition to a low-carbon energy system and are at the core of most energy-climate policies worldwide [77]. For instance, the price decline of PV cells from 3.37 USD/W to 0.48 USD/W in the last 10 years [78] has made solar energy an economic option independent of subsidies.

3.3.1. New technologies
Development of new technologies have made additional renewable energy supply sources available such as advanced biofuels, blue hydrogen, deep geothermal, wave, and seaweed. It also provides innovative opportunities for the further integration of the energy system by implementing P2X technologies, which mainly consist of P2Heat, P2G, P2H2, P2L, and P2Mobility technology options. The seasonal variation of wind and solar increases the need for seasonal storage options such as thermal energy storage and CAES. CCS and CCU technologies can be considered as alternative solutions for conventional GHG emission emitters. Deep decarbonization of the industrial sector can be achieved by the development of new industrial processes while considering the whole value chain [79]. The development of zero energy buildings [80] and formation of energy-neutral neighborhoods [81] can contribute to substantial energy savings in the built environment.

3.3.2. Technological learning
ESMs currently represent technological learning either exogenously or endogenously [82]. Technological change is prevalently expressed as a log-linear equation relating technology cost to its cumulative production units. This one-factor equation provides the learning rate, which is the cost reduction that results from doubling the cumulative produced units of the concerned technology [83]. The prominent alternative is the two-factor equation that incorporates both cumulative produced units and R&D investments [84]. Endogenous Technological Learning (ETL) is widely used in long-term ESM analysis (e.g., see Ref. [85–87]). ETL can be further elaborated as Multi-Cluster Learning (MCL) and Multi-Regional Learning (MRL) [88]. MCL (or so-called Compound Learning) describes a cluster of technologies, which share the same component and learn together (e.g. see Ref. [89]). MRL differentiates between region-specific technological learning and global technological

\[ N = 2 + \text{PV} \]
learning. The consideration of new technologies and technological learning can greatly affect the energy system modeling results, particularly in long-term models. For instance, Heuberger et al. [90] concluded that the presence of global ETL will result in 50% more economically optimal offshore wind capacity by 2050.

3.3.3. Energy efficiency

As part of the Clean Energy for all Europeans package, the EU sets binding targets of at least 32.5% energy efficiency improvement by 2030, relative to the business as usual scenario [91]. This policy emphasizes particularly the built environment as the largest energy consumer in Europe. Although energy-efficient technologies provide financial and environmental costs reduction, they are not widely adopted by energy consumers. This “energy efficiency gap” can be a consequence of market failures, consumer behavior, and modeling and measurement errors [92]. Energy efficiency policies may induce the rebound effect (or backfire), in which energy efficiency improvements lead to an increase in energy use. The rebound effect may have a direct decreasing impact in energy consumption (e.g., a decrease in residential energy consumption), while having an indirect increasing impact (e.g., an increase in energy use by expansion of energy-intensive industries) [93]. Providing an accurate estimate of the magnitude of the rebound effect can be challenging ( [94], while the existence of this effect is a matter of discussion in the literature [95]. Although energy-efficient technologies can play an effective role in energy system transition, modeling and analyzing its direct and indirect effects is challenging.

3.4. Energy infrastructure

Energy infrastructure has a key role in the low-carbon energy system transition by facilitating sectoral coupling, integrating renewable energies, improving efficiency, and enabling demand-side management. However, analyzing energy infrastructure can come up with some challenges, such as the complexities of distributing costs and benefits of investments and allocation of risk between investors and consumers [96]. Conventional energy infrastructure facilities are usually managed by a monopoly as public goods are not traded in a market. Therefore, the clear disaggregation of costs and benefits of infrastructure changes due to energy transition needs further evaluation [97]. Long-term infrastructure investment and risk profiles of investors and consumers can be highly diverse as energy infrastructures can undergo drastic changes. Moreover, social acceptance of energy infrastructure plays a key role in energy transition, particularly in decentralized infrastructures such as CCUS networks, transmission lines, district heating, and local energy storage. Modeling the social acceptance of energy infrastructure requires a combination of qualitative and quantitative datasets which can be highly locally dependent [98].

Assuming the above-mentioned datasets are available, ESMs would require specific capabilities to analyze energy infrastructure. The ESM should be geographically resolved, as energy infrastructure can have both local and national scales. Moreover, there is a need for GIS-based geometrical resolution of ESMs as costs and benefits of energy infrastructures can change drastically by their geographical location.

3.5. Decentralization

Over the past decades, energy used to be supplied by large power plants and then transmitted across to the consumers. By emerging renewable energy supplies, a new alternative concept of the energy system has been developed. The decentralized energy system, as the name suggests, is comprised of a large number of small-scale energy suppliers and consumers. A transition from a centralized fossil-fuel and nuclear-based energy system to a decentralized energy system based on intermittent renewable energy sources can be a cost-effective solution for Europe [99]. The local energy supply reduces transmission costs, transmission risks, environmental emissions, and to some extent promotes energy security for a sustainable society, with a competitive energy market. On the other hand, it can increase generation costs capacity investment, distribution, and energy reliability. Therefore, there is a need to determine the optimal role of energy system decentralization by carefully analyzing costs and opportunities.

Conventional energy modeling tools were based on the centralized energy system and they have faced difficulties fulfilling the decentralized energy system demands. In conventional energy models, the location of the power plants does not play an important role, while spatial detail may be critically important for renewables. For instance, economic potentials, solar potentials, generation costs, environmental and social impacts, network constraints, and energy storage potentials are some location-dependent factors that can vary greatly across different regions. Some other factors such as wind potential and infrastructural costs can vary greatly even with little dislocation. Therefore, a fine spatial resolution is required in order to assess the role of location-dependent parameters in the energy system.

ESMs can use national, regional, or GIS (Geographical Information System) based spatial resolution. Using a fine spatial resolution can be limited by the available computational power and spatial data. Therefore, the choice of spatial resolution is the compromise between these two parameters. Due to the huge computational load of GIS-based ESMs, they are usually applied at urban level rather than national level. GIS-based models can be used in a preprocessing phase in order to provide spatially resolved datasets for national ESMs. For instance, the global onshore wind energy potential dataset is produced at approximately 1 km resolution [100]. Assuming the availability of spatial data, the computational limitation can be addressed by linking a coarse resolution energy model with a spatial modeling tool such as ArcGIS (e.g., see Ref. [101]).

3.6. Human behavior

Conventional energy models neglected social stakeholders as the energy system was managed and controlled by central decision-makers. In order to reach a sustainable low-carbon energy system, technical and social insights should be integrated into these models [102,103]. According to the technology review of the U.S. Department of Energy, the balance of energy supply and demand is affected as much by individual choices, preferences, and behavior as by technical performance [104]. The reliability of energy models is often low because they are excessively sensitive to cost analysis while ignoring major energy policy drivers such as social equity, politics, and human behavior [105]. Several studies have recently indicated the role of social sciences in energy research [106,107]. Social parameters are usually difficult to quantify, and consequently, are usually neglected in quantitative energy models. However, there are practical methods of integrating human aspects into technical energy models, such as the inclusion of prosumers and agent-based modeling.

Originally coined by Alvin Toffler in his 1980 book The Third Wave [108], prosumer is the mixture of the words producer and consumer, explaining the active role of energy consumers in the production process. The conventional energy grid was dependent on the interaction between supplier and distributor, while consumers play an active role in the decentralized energy system. An important element of this new system is the role of prosumers i.e., consumers who also produce and share surplus of renewable energy generated with the grid and/or other consumers in the community [109]. With the emerging renewable energies at the microscale, prosumers are not only an important stakeholder of the future smart grids but may also play a vital role in peak demand management [110]. However, social acceptance of the decentralized energy system faces several drivers and barriers [111] that need quantification in order to be imported into energy models. The emergence of prosumers has increased the diffusion of social sciences in energy system modeling (e.g., see Refs. [112–115]). In order to grasp an adequate knowledge of the decentralized energy system, the behavior of
the prosumers on energy grid should thus be considered alongside the techno-economical characteristics (e.g., see Ref. [116–118]).

Based on the position of the decision-maker, ESMs can be divided into two main categories. The common approach is the assumption of a system planner who optimizes the single objective function (e.g., system cost minimization). Contrary, agent-based models practice decentralized decision making by assuming autonomous agents who decide based on their own objectives. Agent-based modeling has been proposed as a suitable modeling approach for complex socio-technical problems [119] and it is used in modeling the wholesale electricity market considering human complexities [120]. Ringler et al. reviewed agent-based models considering demand response, distributed generation, and other smart grids paradigms [121]. The term “Agent” can be used to describe different types of players in the energy system such as prosumers, power generators, storage operators, or policy makers. Agents can optimize their own objective function, which can be based on economic (e.g., capital, NPV, and tariffs), technical (e.g., efficiency, emissions, and maximum capacity), and social (e.g., bounded rationality, neighborhood effect, and heterogeneity) factors. Including techno-economic factors in the objective function is relatively easier due to the quantitative nature of these parameters, while integrating qualitative social parameters remains a complicated task. Qualitative parameters such as the perceived weight of environmental costs and impacts, expected utilities, social networks, and communication can be estimated by socio-demographic factors and behavior curves (e.g., see Ref. [122–124]).

3.7. Capturing economic interactions

Macroeconomic models follow a top-down analytical approach compared to techno-economic ESMs that use a Bottom-up approach. The analytical approach is the way to break a system into elementary elements in order to understand the type of interactions that exist between them. This system reduction may be done in different ways. Based on the reduction approach, ESMs are usually differentiated into three main groups: Top-down, Bottom-up, and Hybrid models.

Top-down (TD) models describe the energy-economy system as a whole to assess the energy and/or climate change policies in monetary units [125]. These models mainly describe the relations between the energy system and the variations in macroeconomic and environmental factors such as economic growth, demographics, employment rate, global warming, and GHG emissions. Consequently, top-down models lack detail on current and future technological options which may be relevant for an appropriate assessment of energy policy proposals [126]. Macroeconomic equilibrium models are an example of top-down models.

Bottom-up (BU) models, provide a higher degree of technological detail (in comparison to top-down models). Characterized by a rich description of the current and prospective energy supply and end-use technologies, bottom-up models describe energy systems evolutions as resulting from a myriad of decisions on technology adoption [127]. They can compute the least-cost solution of meeting energy balances subject to various systems constraints, such as exogenous emission reduction targets [128].

Hybrid models (i.e., linking TD and BU models) can be a solution to integrate top-down consistency while maintaining bottom-up detail. The major advantage of top-down models is their consistency with welfare, market, economic growth, and other macroeconomic indicators that leads to a comprehensive understanding of energy policy impacts on the economy of a nation or a region. On the other hand, they lack an appropriate indication of technological progress, energy efficiency developments, non-economical boundaries of the system, and other technical details. Instead, bottom-up models describe the energy system with detailed technological properties. Moreover, bottom-up models lack feedback from the macro-effects of the technical changes in the overall economy. Therefore, closing the gap between top-down and bottom-up energy models results in more consistent modeling outcomes (e.g., see Ref. [129–132]).

Model linking is not an exclusive solution for TD and BU models. Hourcade et al. [133] argued that the three main dimensions of an energy-economy system are: technological explicitness, microeconomic realism, and macroeconomic completeness. The main advantage of model linking (i.e., modeling suite) is the ability to provide consistent results while considering two or all three dimensions. Each of these dimensions can be modeled with a number of different models depending on the complexity of the problem.

The model linking approach can be classified into three subcategories, based on the level of linking [135]. First, individual stand-alone models are linked together manually meaning that the processing and transferring of the information between models are controlled by the user, preferably in an iterative manner (i.e., soft-linking). Second, a reduced version of one model exchanges data with the master model while both running at the same time (i.e., hard-linking). Third, a combined methodology features an integrated model through a unified mathematical approach (e.g., mixed complementarity problems [136]), (Fig. 3) Helgesen [134] used another classification based on the linking type of models and the terminology proposed by Wene (i.e., soft-linking and hard-linking) [137]. The advantages of soft-linking can be summarized as practicality, transparency, and learning, while the advantages of hard-linking are efficiency, scalability, and control [138].

3.8. Summary

The above discussion of the main challenges of the present and future ESMs identified several required modeling capabilities, which are summarized in Table 3.

In order to review models based on mentioned challenges, required capabilities are grouped into several model assessment criteria in Table 4. It should be noted that the integrated energy system analysis capability is not mentioned further as all reviewed models were integrated. Moreover, the linking ESMs with TD models’ capability is discussed further in Section 5.

Apart from the criteria that results from emergent challenges of future ESMs, three additional criteria are considered in Table 4, namely: (i) the underlying methodology of the model to separate calculator models from non-calculator ones; (ii) the source of the model’s datasets to measure input-data quality; and (iii) the accessibility and the number of the model’s applications to determine the models’ use and acceptance.

![Fig. 3. Model linking based on the linking degree. Source [134].](attachment:image.png)
### Table 3
Summary of integrated energy modeling challenges and required modeling capabilities.

| Challenges                              | Required modeling capabilities |
|-----------------------------------------|--------------------------------|
| Intermittency and flexibility           | Flexibility options (Storage, DSM, VRE Curtailment, Conventional generation, Cross border trade) |
|                                        | Fine temporal resolution (HTR, HTR time-slices + ChO, HTR time-slices) |
| Further electrification                 | Integrated energy system analysis |
|                                        | Sectoral coupling technologies (P2Mobility, P2Heat, P2Gas) |
|                                        | Seasonal Storage (PHES, CAES, TES, LHES) |
| New technologies and technological change| The granularity of presented technologies (current basket of technologies, P2X family, new renewable sources, and storage options) |
|                                        | Technological learning (exogenous, 1-factor ETL, multi-factor ETL, MCL, MRL) |
| Decentralization                        | Fine spatial resolution (national, regional, GIS) |
| Human behavior                          | Socio-economic parameters (demand profile, learning, risk profile, communication with others, perceived environmental value, and perceived discount factor) |
| Macroeconomic interactions              | Linking ESMs with TD models (soft-link, hard-link, integrate) |

### Table 4
Assessment criteria based on modeling capabilities and our suggestions.

| Capabilities                              | Criteria                                                        |
|-------------------------------------------|-----------------------------------------------------------------|
| • Flexibility options (Storage, DSM, Cartailment, Conventional generation, Cross border trade) | Technological detail and learning |
| • Seasonal Storage (PHES, CAES, TES, HES) | Temporal resolution |
| • Sectoral coupling technologies (P2Mobility, P2Heat, P2Gas) | Spatial resolution |
| • The granularity of presented technologies (current basket of technologies, P2X family, new renewable sources, and storage options) | Social parameters |
| • Technological learning (exogenous, 1-factor ETL, multi-factor ETL, MCL, MRL) | Modeling methodology |
| • Fine temporal resolution (HTR, HTR time-slices + ChO, HTR time-slices) | Data use |
| • Fine spatial resolution (national, regional, GIS) | Accessibility and Application |
| • Human behavior (agent type, neighborhood effect, and heterogeneity) | |
| General capabilities                       | |

### 4. The Multi-Criteria Analysis

Considering the criteria regarding the future low-carbon energy systems and available models, it can be concluded that no perfect model exists. Models can be assessed based on the list of criteria such as temporal resolution, spatial resolution, the social aspect, data source quality, accessibility, and application (Table 4).

The capability of the model in each criterion is given a score from five (highest) to one (lowest) as presented in Table 5. The results are highly dependent on the scores and weights, which are both - to some extent - subjective. Readers can alter the results by incorporating new criteria or changing the perspective weights. In the following sections, these modeling capabilities and the corresponding scores are explained.

#### 4.1. Technological detail and learning

There are two parameters that differ across integrated ESMs, which are the inclusion of FOs and the inclusion of technological learning. Therefore, models can be grouped into three groups: (i) no flexibility option and no technological learning that would score one; (ii) the inclusion of either flexibility options or technological learning that would score three; and (iii) the inclusion of flexibility options and technological learning that would score five.

#### 4.2. Temporal resolution

ESMs usually balance the supply and demand on a yearly basis or a limited amount of (hourly) time-slices per year. Nevertheless, some models have a higher temporal resolution and balance the system on an hourly basis. Reviewed models can be categorized in three groups: (i) temporal resolution on yearly basis that would score one; (ii) time-slice approach that would score three; and (iii) hourly temporal resolution that would score five.

#### 4.3. Spatial resolution

Some models have the capability to model the regions inside a country. This ability can provide regional insights on energy system policies and vice versa. Although the limited computational capacity and the lack of data make it difficult to perform a detailed regional analysis, some models balance the system in different regions inside the country based on different capacities and properties of the regions (e.g., ESME in the UK). Reviewed models are divided in three groups: (i) models without regional depth that would score one; (ii) models which consider regions that would score four, since it is a considerable improvement; and (iii) models which consider GIS data that would score five.

#### 4.4. Social parameters

The role of social analysis in techno-economic models is usually negligible. However, some modeling tools practice multi-agent...
programming in order to model qualitative aspects of stakeholders’ decision-making practice on energy systems. Models are categorized into two groups: (i) models capturing socio-economic parameters only based on demand curves that would score one, and (ii) agent-based models considering a set of decision-making rules for different stakeholders in the energy system that would score five.

4.5. Modeling methodology

Reviewed models practice a different set of methodologies. In this review, the main categorization between methodologies can be made between the calculator and non-calculator methodologies. Therefore, models can be grouped into two groups: (i) calculator models that would score one, and (ii) non-calculator models that would score five.

4.6. Data use

The depth of technical detail and the quality of the data play a crucial role in providing accurate insights into the energy system with regard to new technologies and sectoral coupling. Moreover, data access is the first limitation of energy system research as databases are rather private. Models can then be divided into five groups: (i) models not indicating a data source that would score one; (ii) models using generalized open-source data that would score two; (iii) models using limited country-specific data that would score three; (iv) models using detailed open-source data that would score four; and (v) models using detailed country-specific datasets, possibly in combination with global datasets that would score five.

4.7. Accessibility

Open-access models provide an opportunity to test the model and provide feedback. These models are divided into five groups: (i) models which provide no access that would score one; (ii) models which provide limited access that would score two; (iii) models which are commercial that would score three; (iv) models which are open-source but need permission that would score four; and (v) models which are completely open-source and accessible on Internet that would score five.

4.8. Application

A model with more applications and users makes it easier to disseminate and discuss results. Models are grouped in five sets: (i) models with no publication yet that would score one; (ii) models applied in one country that would score two; (iii) models applied in two countries that would score three; (iv) models applied across EU countries that would score four; and (v) models which applied in many countries and are well-known that would score five.

Table 6 demonstrates the MCA analysis with equal weight for all criteria. To calculate the score of each model for each criterion, the weighted percentage of that criterion in the model’s total score is demonstrated. This percentage is calculated endogenously, as explained by (Equation 1). It indicates the share of the models’ score in each criterion out of the models’ total score.

\[
\text{Weighted percentage}_{\text{Model, Criterion}} = \frac{\text{Score}_{\text{Model, Criterion}} \times \text{Weight}_{\text{Model, Criterion}}}{\sum_{c=1}^{n} \left( \text{Score}_{\text{Model, c}} \times \text{Weight}_{\text{Model, c}} \right)}
\]

(Equation 1)

PRIMES would score high mainly due to the inclusion of social parameters, while the high score of REMix is due to its high spatial resolution. These models merely demonstrate improved capabilities compared to others; therefore, it does not mean that these models are “best” models. Moreover, some features of the models are not reflected in this table. For instance, METIS works complementary to long-term ESMs as it only simulates one specific year. Besides, the MCA results can be changed considerably by assigning slightly different scores to various criteria as total scores are relatively close. Models such as the MARKAL family and METIS demonstrate high scores mainly due to their high granularity; however, they lack the inclusion of social parameters. ENSYSI includes social parameters while lacking spatial resolution and application.

4.9. Sensitivity analysis

Addressing all the policy-induced challenges of the energy system requires a comprehensive ESM that is not yet available. Therefore, a compromise should be made based on the challenges that the model is designed to address.

Consequently, a weighted decision matrix can be formed by using the AHP method [139]. In this method, the criteria are rated against each other with respect to the challenges. A consistency ratio (CR) is calculated to indicate the reliability of the weight table. Saaty suggests that the CRs of more than 0.1 are too inconsistent to be considered reliable [139]. Here the challenges are divided into two main groups, first: intermittency, flexibility, and further electrification; and second: human behavior and decentralization. The first group of challenges puts emphasis on the technological detail, the high temporal and spatial resolution; while the second group emphasizes the inclusion of social parameters and high spatial resolution.

The pair-wise weighted decision matrix for the first group of challenges is formed in Table 7. In each row, the importance of a criterion compared to other criteria is given a number in this order: 1 would be equal importance, 3 would be fairly important, and 5 would be extremely important. It should be noted that these numbers are entirely subjective, thus, the user can make his own decision matrix. Then, the table is normalized and the sum of each row is reported as the weight of the criterion. To calculate the CR, each column of the pair-wise table is multiplied by the corresponding weights. Then, the sum of each row is divided by the corresponding weight to get λ values. The CR is then calculated by Equation (2), in which n is the number of criteria.

\[
CR = \frac{\lambda_{\text{average}} - n}{n - 1}
\]

(Equation 2)

Repeating the same procedure for the second group of challenges leads to Table 8. In both cases, the low CR indicates low levels of inconsistency in the assigned weights.

Using the weights in Table 8 to update the MCA will lead to a slightly different result, presented in Table 9. For the first group, it is expected that models with high scores in technological detail, temporal resolution, and spatial resolution will get higher total scores. The REMix model gets a high total score mainly due to the inclusion of high spatial resolution with the use of GIS data and the inclusion of key flexibility and storage technologies with the exogenous technological learning. The METIS model provides lower technological detail by neglecting technological learning while incorporating hourly temporal resolution and GIS-based spatial resolution. For the second group, the inclusion of social parameters and fine spatial resolution gains importance. Models with the inclusion of social parameters such as PRIMES and ENSYSI get higher scores. Although the METIS model does not include social parameters, it keeps a high score due to its fine spatial resolution.

Irrespective of the assigned weights, we find four models at the top of the MCA table which are REMix, PRIMES, METIS, and the MARKAL family models. These models had high scores in nearly all criteria, while a low score in one criterion (for instance, lack of social parameters for REMix) is compensated with a high score in another criterion (high temporal and spatial resolution). These four models were either developed recently (e.g., REMix and METIS) or are under constant development (e.g., MARKAL family and PRIMES). It shows how integrated energy system modeling points towards the models with improved capabilities in all the criteria.

Other models keep the same ranking position except for IWES,
ENSYSI, and EnergyPLAN, which changed their position considerably (i. e., more than two steps change). This position change can be explained by the asymmetry of these models’ scores in the MCA table. For instance, the IWES model gets a high score in the first four criteria while getting a low score in the last four criteria.

The MCA represents an overview of the current state of ESMs with regard to low-carbon energy system modeling challenges. However, there is a need for adding new capabilities to current ESMs in order to address future modeling challenges. In the next section, we discuss two potential modeling solutions based on our observation from the current state. The overall solution is to expand single models and/or to link different models.

5. Developing and linking models

It is not practical to decide on the best model that addresses challenges regarding low-carbon energy systems, as each model has specific pros and cons. From a techno-economic point of view, the MCA indicates that for modeling the low-carbon energy system, current models require specific capabilities such as hourly temporal resolution, regional spatial resolution, inclusion of sectoral coupling technologies, technological learning, and inclusion of social parameters. There are major gaps between policy questions and modeling capabilities in the criteria, which were used to assess the models’ performance. However, these criteria mainly focus on the technical policy questions rather than the entire technical, microeconomic, and macroeconomic aspects. Although techno-economic models are rich in detail, they lack the capability to answer microeconomic and macroeconomic policy questions. Therefore, specific models, such as energy market models and general equilibrium models, have been developed. Due to the strong interconnection between energy and economy, mixed policy questions arise that require analyzing the technical, microeconomic, and macroeconomic aspects.

Note: Percentages may not add up to 100 due to rounding.

Table 6
The MCA analysis table with equal weights.

| Model name | Modeling methodology | Technological detail | Temporal resolution | Spatial resolution | Social parameters | Data source | Accessibility | Application | Total |
|------------|----------------------|---------------------|---------------------|-------------------|-------------------|-------------|---------------|-------------|-------|
| PRIMES     | 5 15%                | 5 15%               | 3 9%                | 4 12%             | 5 15%             | 4 12%       | 3 9%          | 4 12%       | 4.13  |
| REMix      | 5 15%                | 5 15%               | 3 9%                | 5 15%             | 1 3%              | 5 15%       | 4 12%         | 5 15%       | 4.13  |
| MARKAL f.  | 5 16%                | 5 16%               | 3 9%                | 4 13%             | 1 3%              | 4 13%       | 5 16%         | 5 16%       | 4.00  |
| METIS      | 5 16%                | 3 10%               | 5 16%               | 5 16%             | 1 3%              | 4 13%       | 3 13%         | 4 13%       | 3.88  |
| ENSYSI     | 5 17%                | 3 10%               | 5 17%               | 1 3%              | 5 17%             | 4 14%       | 1 3%          | 3 13%       | 3.63  |
| GSeMOSYS   | 5 18%                | 5 18%               | 3 11%               | 4 14%             | 1 4%              | 2 7%        | 5 18%         | 3 11%       | 3.50  |
| OPERA      | 5 19%                | 5 19%               | 3 12%               | 1 4%              | 1 4%              | 5 19%       | 4 15%         | 2 8%        | 3.25  |
| NEMS       | 5 19%                | 5 19%               | 1 4%                | 4 15%             | 1 4%              | 4 15%       | 4 15%         | 2 8%        | 3.25  |
| POLES      | 5 19%                | 5 19%               | 1 4%                | 4 15%             | 1 4%              | 4 15%       | 2 8%          | 4 15%       | 3.25  |
| SimREN     | 5 19%                | 3 12%               | 5 19%               | 4 15%             | 1 4%              | 5 19%       | 1 4%          | 2 8%        | 3.25  |
| EnergyPLAN | 1 4%                 | 3 12%               | 5 20%               | 1 4%              | 1 4%              | 5 20%       | 5 20%         | 4 16%       | 3.13  |
| ESMЕ        | 5 21%                | 3 13%               | 3 13%               | 4 17%             | 1 4%              | 5 21%       | 1 4%          | 2 8%        | 3.00  |
| IWES       | 5 21%                | 3 13%               | 5 21%               | 4 17%             | 1 4%              | 3 13%       | 1 4%          | 2 8%        | 3.00  |
| STREAM     | 1 4%                 | 3 13%               | 5 22%               | 4 17%             | 1 4%              | 2 9%        | 5 22%         | 2 9%        | 2.88  |
| ETM        | 1 5%                 | 3 16%               | 5 26%               | 1 5%              | 5 1%              | 2 11%       | 4 21%         | 2 11%       | 2.38  |
| LEAP       | 1 5%                 | 1 5%                | 1 5%                | 4 21%             | 1 5%              | 4 21%       | 3 16%         | 4 21%       | 2.38  |
| E4Cast     | 5 28%                | 1 6%                | 1 6%                | 4 22%             | 1 6%              | 3 17%       | 1 6%          | 2 12%       | 3.18  |
| DyEMo      | 1 6%                 | 3 18%               | 5 29%               | 1 6%              | 1 6%              | 5 29%       | 1 6%          | 2 12%       | 2.13  |
| IKARUS     | 5 29%                | 1 6%                | 1 6%                | 1 6%              | 1 6%              | 5 29%       | 1 6%          | 2 12%       | 2.13  |
| Weights    | 1                   | 1                   | 1                   | 1                 | 1                 | 1           | 1             | 1           | 8     |

Table 7
Weighted decision matrix for the first group of challenges.

| CR – 0.05 | Modeling methodology | Technological detail | Temporal resolution | Spatial resolution | Social parameters | Data source | Accessibility | Application | Weight |
|-----------|----------------------|----------------------|---------------------|-------------------|-------------------|-------------|---------------|-------------|--------|
| Modeling methodology | 1                   | 1/3                  | 1/5                  | 1/2                | 3                 | 1/2         | 1             | 1           | 0.07   |
| Technological detail     | 3                   | 1                    | 1/2                  | 3                  | 5                 | 3           | 4             | 4           | 0.23   |
| Temporal resolution     | 5                   | 2                    | 1                    | 3                  | 5                 | 3           | 5             | 5           | 0.30   |
| Spatial resolution      | 2                   | 1/3                  | 1/3                  | 1                  | 4                 | 2           | 4             | 4           | 0.15   |
| Social parameters       | 1/3                 | 1/5                  | 1/5                  | 1/4                | 1                 | 1/3         | 1/2           | 1/2          | 0.04   |
| Data source             | 2                   | 1/3                  | 1/3                  | 1/2                | 3                 | 1           | 3             | 3           | 0.11   |
| Accessibility            | 1                   | 1/4                  | 1/5                  | 1/4                | 2                 | 1/3         | 1             | 2           | 0.06   |
| Application             | 1                   | 1/4                  | 1/5                  | 1/4                | 2                 | 1/3         | 1/2           | 1           | 0.05   |
| Sum                     | 15.33               | 4.70                 | 2.97                 | 8.75               | 25.00             | 10.50       | 19.00         | 20.50       | 1      |

Table 8
The weight table of two groups of challenges for the MCA.

| Challenges                              | Modeling methodology | Technological detail | Temporal resolution | Spatial resolution | Social parameters | Data source | Accessibility | Application | CR |
|-----------------------------------------|----------------------|----------------------|---------------------|-------------------|-------------------|-------------|---------------|-------------|-----|
| Intermittency, flexibility, and further electrification | 0.07                 | 0.23                 | 0.3                 | 0.15              | 0.04              | 0.11        | 0.06          | 0.05        | 0.05 |
| Human behavior and decentralization     | 0.05                 | 0.11                 | 0.13                | 0.19              | 0.33              | 0.09        | 0.06          | 0.04        | 0.06 |
computational limitation can be addressed either by hardware or software development. Fig. 4. Approach for single model development. Source [140].

Table 9
Changes in the MCA analysis table based on perspective weights.

| Equal weights | First group perspective | Second group perspective |
|---------------|-------------------------|-------------------------|
| REMix         | REMix                   | PRIMES                  |
| PRIMES        | METIS                   | ENSYSI                  |
| MARKAL f.     | MARKAL f.               | Remix                   |
| METIS         | PRIMES                  | METIS                   |
| ENSYSI        | SimRENS                 | MARKAL f.               |
| OSeMOSYS      | ENSYSI                  | SimRENS                 |
| SimRENS       | OSeMOSYS                | OSeMOSYS                |
| NEMS          | IWES                    | IWES                    |
| POLES         | STREAM                  | NEMS                    |
| OPERA         | EnergyPLAN              | STREAM                  |
| EnergyPLAN    | OPERA                   | POLES                   |
| IWES          | ESME                    | ESME                    |
| ESME          | NEMS                    | OPERA                   |
| STREAM        | POLES                   | EnergyPLAN              |
| ETM           | ETM                     | LEAP                    |
| LEAP          | DynEMo                  | ETM                     |
| DynEMo        | E4Cast                  | DynEMo                  |
| IKARUS        | IKARUS                  | IKARUS                  |

Some common energy system modeling methodologies are optimization, simulation, accounting, multi-agent, and equilibrium. Each mathematical methodology can be developed to answer specific energy modeling questions. Integrating two different methodologies can form a modeling suite that involves four different models, namely, the Energy System Model (ESM), the Energy Market Model (EMM), the Macroeconomic Model (MEM), and the Socio-Spatial Model (SSM). The core component of the suggested modeling suite is the presence of different modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs combined with energy market models (i.e., unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as the identification of connection points in soft-linking (e.g., see Ref. [142]), convergent solution in soft-linking (e.g., see Ref. [143]), and mathematical formulation for integrated linking (e.g., see Ref. [144, 145]). In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

5.2. Linking models

An alternative approach to overcome the limitations of single model development is to form a modeling suite. Model linking can be done between any set of desired models in order to enhance modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs combined with energy market models (i.e., unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as the identification of connection points in soft-linking (e.g., see Ref. [142]), convergent solution in soft-linking (e.g., see Ref. [143]), and mathematical formulation for integrated linking (e.g., see Ref. [144, 145]). In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

5.2.1. A: the core ESM

The core component of the suggested modeling suite is the presence of different modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs combined with energy market models (i.e., unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as the identification of connection points in soft-linking (e.g., see Ref. [142]), convergent solution in soft-linking (e.g., see Ref. [143]), and mathematical formulation for integrated linking (e.g., see Ref. [144, 145]). In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

5.2.2. B: the connected ESMs

Model linking can be done between any set of desired models in order to enhance modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs combined with energy market models (i.e., unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as the identification of connection points in soft-linking (e.g., see Ref. [142]), convergent solution in soft-linking (e.g., see Ref. [143]), and mathematical formulation for integrated linking (e.g., see Ref. [144, 145]). In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

5.2.3. C: the full modeling suite

Model linking can be done between any set of desired models in order to enhance modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs combined with energy market models (i.e., unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as the identification of connection points in soft-linking (e.g., see Ref. [142]), convergent solution in soft-linking (e.g., see Ref. [143]), and mathematical formulation for integrated linking (e.g., see Ref. [144, 145]). In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.
Table 10
Model development and model linking suggestions based on the identified energy modeling gaps.

| Current energy system modeling gaps                                                                 | Suggestions                                                                 |
|-----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Lack of sectoral coupling technologies between electricity, heat, and transport sectors.           | Developing a long-term planning optimization Energy System Model (ESM) that involves all energy sectors, hourly temporal resolution, regional spatial resolution, seasonal storage options, and technological learning. |
| Lack of new seasonal storage technology options such as TES and HES.                               | Hard-linking ESM with a Regional Energy System Model (RESM) that involves resolved spatial resolution, land use analysis, and infrastructure analysis. |
| Lack of endogenous technological learning rates.                                                   | Developing an ABM simulation Socio-Technical Energy Model (STEM) that involves stakeholders’ behavior, local and neighborhood effects, bounded rationality, and perceived environmental values. |
| Lack of hourly temporal resolution for capturing intermittent renewables and corresponding potentials.| Hard-linking ESM with an international (or European) Energy Market Model (EMM) that involves an optimal dispatch electricity market, the gas and oil market, hourly temporal resolution, regional spatial resolution, and a detailed generation database. |
| Lack of regional spatial resolution for analyzing energy flows between regions across a country.   | Soft-linking ESM with a Macroeconomic Model (MEM) such as a Computable General Equilibrium (CGE) model that involves the whole economy. |
| Lack of fine geographical resolution options such as GIS, fine mesh, and clustering for analyzing decentralized intermittent supply and infrastructure costs and benefits. |                                                                              |
| Lack of spatially resolved datasets such as infrastructure and local storage.                      |                                                                              |
| Simplistic modeling of human behavior in the current ABMs.                                        |                                                                              |
| The focus of current datasets is only on technological detail, rather than stakeholders’ behavior. |                                                                              |
| High dependence of ESMs on consumer load profiles.                                                |                                                                              |
| Lack of national energy modeling consistency with a European (or an international) energy market. |                                                                              |
| Lack of energy modeling consistency with macroeconomic indicators.                                 |                                                                              |

Fig. 5. Symbolic gap between the results of the simulation and optimization methodologies.

of a central techno-economic ESM as an information processor hub that exchanges the outputs with different models. Based on the current state of the energy system and future scenarios, the ESM can determine the technology and energy mix, commodity and energy prices, amount and price of emissions, and total energy system cost. However, this stand-alone analysis is based on specific scenario assumptions of demand profiles, energy import and export profiles, decentralized energy supply prospects, and macroeconomic expectations. It is suggested to use linear relations (i.e., linear optimization methodology) to keep the computational load manageable.

While the optimization framework determines the theoretically optimal state of the energy system, the simulation methodology can demonstrate feasible pathways to reach the optimal state. Therefore, by comparing the results of the optimization and simulation frameworks, the gap between the optimal solution and the feasible solution (symbolically demonstrated in Fig. 5) can be identified. Several policy parameters can affect the width of this gap by bringing the feasible solution close to the optimal one. Therefore, the analysis of the simulation and the optimization methodologies can provide a better understanding of the role of each parameter in reaching the optimal state of the energy system policy targets.

Based on the review and the MCA, several optimization ESMs such as TIMES and REMix can be used as the core ESM of the modeling suite, due to their fine temporal resolution and ample technological detail. Agent-based simulation ESMs are not as common as optimization ESMs; therefore, from the reviewed models, only ENSYSI and PRIMES can be selected as simulation core ESMs.

5.2.2. B: Hard-linking with the regional model

Current ESMs lack the capability to model the regional implications of the energy system such as decentralized supply and demand, infrastructure costs and benefits, land use, and resource allocation. Although some local energy system models such as EnerGis [146] and GISA SOL [147] provide geographically resolved energy system analysis, they lack the interaction with other country regions. As regional variations of the energy system can have drastic effects on the system itself, it is suggested to hard-link the regional model into the core ESM. The geographical resolution of ESMs can be improved depending on the research questions and available resources. For instance, after identifying spatially sensitive parameters of the energy system such as heat supply location, renewable power production, transmission capacity expansion, and storage infrastructure, Sahoo et al. provided a framework to integrate them into an ESM (i.e., the OPERA model) [148]. Focusing on infrastructure, Van den Broek et al. clustered the CO2 source regions using the ArcGIS software and then incorporated the spatially resolved data into the MARKAL-NL-UU as the optimization-based ESM [149].

5.2.3. C: Hard-linking with the energy market model

For well-connected countries, it is suggested to hard-link an EMM with the core ESM to capture the flexibility potential of the cross-border energy trade, albeit some studies that use a soft-linking approach (e.g., see Ref. [150,151]). In particular, for EU countries, this hard-linking is necessary as the interconnection Flexibility Option (FO) can be in direct competition with domestic FOs such as demand response or storage. EMMs usually use the MILP underlying methodology in order to model unit commitment; therefore, the inclusion of EMM inside ESM can be computationally intensive. It is suggested to use a linear optimization methodology in accordance with the core ESM to reduce computational load, while reaching a fair estimate of the energy import and export flows, particularly for electricity.

5.2.4. D: Soft-linking with a macroeconomic model

Assuming the regional and interconnection capabilities are integrated into the core ESM, in order to capture consistent economic analysis, one soft-linking loop is suggested as follows. This loop incorporates a macroeconomic model, which keeps demand and supply of commodities in equilibrium based on the statistical economic data such as capital stocks and investments, demographics, labor market, and trade and taxes. The ESM outputs, such as energy prices, energy mix, and emissions are fed into the MEM to update the supply and demand and price data of energy and fuel commodities. The MEM provides the equilibrium demographics, GDP and income, monetary flows between economic sectors, trade, and employment rate. This loop can be performed once or it can continue until the results reach a convergence criterion, which is a user-defined criterion that determines the maximum gap between the results of two models.

Moreover, MEM outputs can feed into an ABM simulation ESM in
which consumer demand profiles are generated based on demographics, income, and employment (e.g., see Ref. [152]). The STESM analyzes the social aspects of the energy system such as stakeholders’ behavior, bounded rationality, imperfect communication, and environmental perceived value.

The choice of models, connection points, and scenarios are dependent on the aims of the energy system modeling, available expertise and resources, and access to models and datasets.

6. Conclusion

In summary, we identified the capabilities and shortcomings of current ESMs to analyze adequately the transition towards a low-carbon energy system. In this regard, we described seven current and future low-carbon energy system modeling challenges. Finally, to bridge major energy modeling gaps, two conceptual modeling suites are suggested, based on both optimization and simulation methodologies, in which the integrated ESM is hard-linked with a regional model and an energy market model and soft-linked with a macroeconomic model. Model development and linking choices can be affected by major changes in the energy system outlook. For instance, the current COVID-19 situation can have major impacts on economic activities, indicating the importance of soft-linking with macroeconomic models.

A limitation of this study is that all the information about models has been gathered from published documents, which might be outdated as models are constantly under development. Therefore, this review provides a rather static view on ESMs. Only a limited number of energy system models was presented in this review, which is mainly due to limited time, resources, and access to modeling databases. Other challenges of low-carbon energy systems modeling not included here are the need for energy policy harmonization, energy market design, business models of new technologies, legislation and legal aspect of the energy transition, and social acceptance implications of the energy transition. Another limitation of this study is the subjective assignation of scores with the MCA, however, a clear explanation for the assignation of scores was provided. Furthermore, the MCA only considered single ESMs while in practice a combination of models can be analyzed. A more comprehensive MCA would consider the capabilities and limitations of suites of models.

Declaration of competing interests

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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Appendix A. Supplementary data

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