A systemic approach to analyze integrated energy system modeling tools, a review of national models

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Abstract

This paper reviews academic 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 some derived criteria, and (iii) discuss briefly some potential solutions to address the ESM gaps.

This paper delivers three main outcomes. First, to identify key criteria for analyzing current ESMs, seven current and future low-carbon energy system modeling challenges are described, namely, 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 in some models such as 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 both a regional model and an energy market model and soft-linked with a macroeconomic model.

Highlights:

- Seven low-carbon energy system modeling challenges are described
- Multi-Criteria Analysis is used as a framework to identify modeling gaps
- Some potential solutions to address the ESM gaps are briefly discussed
- Two conceptual modeling suites are suggested to bridge major energy modeling gaps

Keywords

Future energy systems, Energy system model, Energy modeling challenges, Multi-criteria analysis, Soft-linking models, Hard-linking models, Model integration

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Abbreviations

Technologies and Methods	
ABM	Agent-Based Modelling
BU	Bottom-up models
CAES	Compressed Air Energy Storage
CCS	Carbon Capture and Storage
CGE	Computable General Equilibrium
DES	Discrete Event Simulation
DP	Dynamic Programming
EV	Electric Vehicle
GIS	Geographic Information System
LP	Linear Programming
MAP	Multi-Agent Programming
MCA	Multi-Criteria Analysis
MCL	Multi-Cluster Learning
MIP	Mixed-Integer Programming
MRL	Multi-Regional Learning
P2H	Power to Hydrogen
P2G	Power to Gas
PV cell	Photo Voltaic cell
SD	System Dynamics
TD	Top-down models

Institutes and Software	
ABARE	Australian Bureau of Agricultural and Resource Economics
ADEME	French Environment and Energy Management Agency
AIMMS	Advanced Integrated Multidimensional Modeling Software
DEA	Danish Energy Agency

DG ENER	Directorate-General for Energy (European Commission)
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DTU	Danmarks Tekniske Universitet (Technical University of Denmark)
ECMWF	European Centre for Medium-range Weather Forecasts
ECN	Energy research Centre of the Netherlands (ECN part of TNO)
EIA	U.S. Energy Information Administration
EMOS	Energy Market Observation System
ENTSO-E	European Network of Transmission System Operators for Electricity
ENTSO-G	European Network of Transmission System Operators for Gas
ETSAP	Energy Technology Systems Analysis Program
ETI	Energy Technology Institute
GAMS	General Algebraic Modeling System
GEA	Global Energy Assessment
IEA	International Energy Agency
IIASA	International Institute for Applied Systems Analysis, Austria
IPCC	Intergovernmental Panel on Climate Change
ISEP	Institute for Sustainable Energy Policies (Japan)
IRENA	International Renewable Energy Agency
ISUSI	Institute for Sustainable Solutions and Innovations
MONIT	Monitoring Ontwikkeling Nationaal verbruik, Informatie en Trendanalyse (Netherlands)
NEO	National Energy Outlook (Netherlands)
OFCE	French Economic Observatory
TNO	Nederlandse Organisatie voor Toegepast Natuurwetenschappelijk Onderzoek (Netherlands Organization for Applied Scientific Research)
UNFCCC	United Nations Framework Convention on Climate Change
WEC	World Energy Council
WBGU	German Advisory Council on Global Change

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1. Introduction

The long-term energy strategy of the EU is aimed at 80-95% Greenhouse Gas (GHG) emissions reduction by 2050, relative to 1990. Reaching this goal requires a number of key actions intended 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 and growing body of literature has listed and classified ESMs with different aims and scopes. Connolly et al. have provided a comprehensive overview intended to identify suitable ESMs to address issues related to renewable energy integration [2]. Similarly, Bhattacharyya et al. have compared energy models to identify the most suitable model for developing countries [3]. Aiming to find the prevalent modeling approaches for the U.K., Hall et al. have classified and compared ESMs based on their structure, technological detail, and mathematical approach [4]. To find trends in energy system modeling, Lopion et al. have reviewed ESMs in a temporal manner [5]. Some reviews have emphasized the role of policy questions and the corresponding modeling challenges. By grouping energy models in four categories, Pfenniger et al. have examined the policy challenges they face in each paradigm [6]. Horschig et al. have reviewed ESMs to provide a framework for identifying a suitable methodology for the evaluation of renewable energy policies [7]. Likewise, Savvidis et al. have identified the gaps between low-carbon energy policy challenges and modeling capabilities with a focus on electricity market models [8]. Some authors such as Ringkjøb et al. have classified ESMs with a focus on the electricity sector [9], while others such as Li et al. have reviewed socio-technical models emphasizing on societal dynamics [10].

The increasing share of Variable Renewable Energy Sources (VRES) 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, efficiency improvements, decentralization, macroeconomic interactions, and the higher involvement of human stakeholders in the energy system transition. Additionally, some policy questions at the macro level, such as the impact of the energy transition on the macroeconomic performance (e.g. economic growth and employment), require more in-depth integrated analysis, i.e. analyzing the whole energy system consisting of technical, microeconomic, and macroeconomic aspects.

However, current ESMs lack specific capabilities for adequately addressing low-carbon energy system changes that can cause debated conclusions. For instance, one study finds that there is no feasible way to achieve a 100% renewable power system by 2050 [11], while another study claims a 100% renewable EU power system scenario with 30% higher annual costs [12]. Connolly et al. suggest that a 100% renewable EU energy system can be achieved by 2050 with 12% higher annual energy system costs [13], while neglecting significant parameters such as the electricity grid costs, location of renewables, key technological detail, and flexible electricity demand. Brouwer et al. provide a detailed analysis of the West European power sector with high shares of renewables, while neglecting the heat and transport sectors [14]. Brown et al. analyze 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, although some studies analyze actors' behavior in the energy system on the demand side; for instance, they investigate the thermal demand transition [16] or the adaptation of efficiency measures of 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 although the transition towards a decarbonized energy system can involve 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. Moreover, due to the diversity of ESMs, two major limitations will be imposed on this review in order to keep it manageable. First, this research paper focuses on energy models at the national level. Therefore, reviewed models are designed for national analysis or they can be used for national assessments (e.g. PRIMES model). Second, reviewed models cover the whole energy system including all the energy 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 modeling challenges?". To answer this question, first, the current and future low-carbon energy system modeling challenges are described. Based on low-carbon energy system modeling challenges, this review identifies 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 are then translated into assessment criteria to be used in Multi-Criteria Analysis (MCA). Finally, potential model development solutions are discussed and a modeling suit is proposed as a model-linking solution to address the energy modeling challenges.

2. Method

Seven major low-carbon energy system modeling challenges were identified and described in Section 3. The challenges were translated into a number of required energy system modeling capabilities and criteria to be used in later sections.

Nineteen models were selected from other reviews in the literature such as Connolly et al. [2] and Hall et al. [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 presented 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 further developed. For each model, a brief description was provided in the Appendix section.

Model	**Developer / Source**	**Model**	**Developer / Source**
DynEMo	UCL / [18], [19]	*METIS*	Artelys / [20]
E4Cast	ABARE / [21]	*NEMS*	EIA / [22]
EnergyPLAN	Aalborg University / [23]	*OPERA*	ECN / [24]
ENSYSI	PBL / [25]	*OSeMOSYS*	KTH, UCL / [26]
ESME	ETI / [27]	*POLES*	Enerdata / [28]
ETM	Quintel Intelligence / [29]	*PRIMES*	NTUA / [30]
IKARUS	Research Center Jülich / [31], [32]	*REMix*	DLR / [33]
IWES	Imperial College London / [34]	*SimREN*	ISUSI / [35]
LEAP	Stockholm Environmental Institute / [36]	*STREAM*	Ea Energy Analyses / [37]
MARKAL, MARKAL-MACRO, TIMES	IEA / [38], [39]		

Table 1, The reviewed models and their corresponding developers

Multi-Criteria Analysis methodology was used as a transparent framework to analyze complex ESMs from different perspectives. MCA is a methodology to analyze complex choices (i.e. various criteria, objectives, and indicators), which has been used extensively for analyzing 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 in tables 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” that was used for structuring the 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 modeling 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.

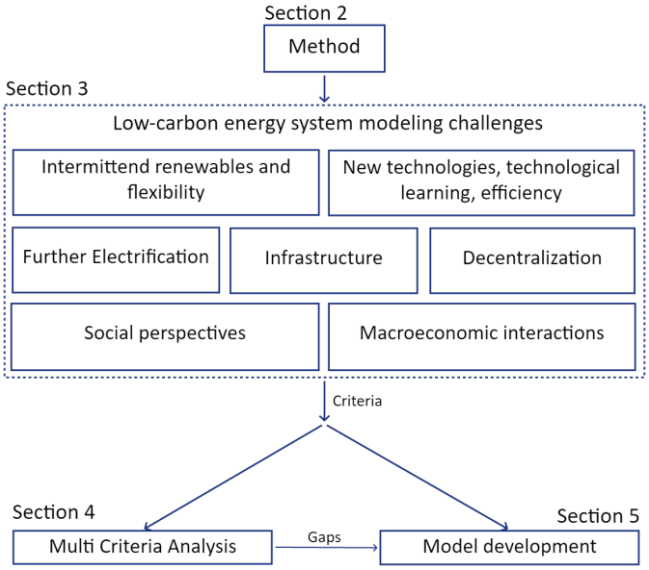

Figure 1, The structure of this study

3. Low-carbon energy system modeling challenges

Energy policies are designed to meet three key objectives of the energy system 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] cluster twelve energy policy questions as a basis to quantify the gap between models and policy questions. Based on the literature and experts' opinions, we divide energy modeling related policy questions into four categories as follows:

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 in economic growth and jobs due to the energy transition.
4. The mix of the above such as lack of insights on the effect of new technologies on energy markets and jobs.

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 take 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.

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 (mainly from wind and solar sources) 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 of FOs' literature review ([49], [50]). An extensive review of different FOs is provided by Lund et al. [51] who list 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] investigate FOs by suggesting three causes of the demand for flexibility as the variability of the residual load, the uncertainty of the residual load, and congestion of the grid. Michaelis et al. [52] divide FOs based on the residual load in three groups, which are downward, upward, and shifting flexibility. Due to high detail and complications regarding each FO, some studies focus mainly on one or a few technologies. To name a few examples: Blanco et al. investigate 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 is investigated by Hers et al. [54] and ISPT [55], respectively. Some other studies follow an integrated approach that includes several FOs in different sectors; however, they have to make several assumptions as the computational capacity is limited (e.g. see [15]).

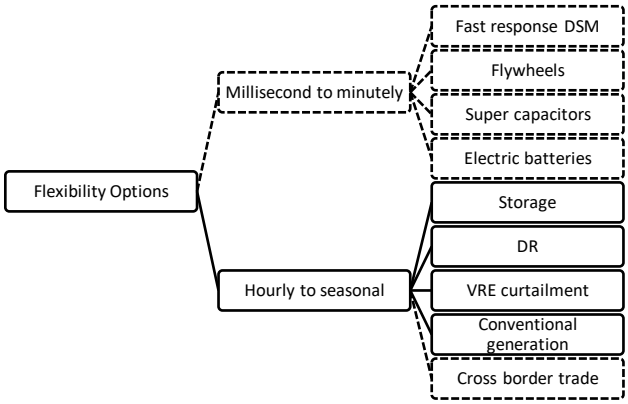

Figure 2, Flexibility options classified by their temporal scale

Note: Dashed options are usually excluded from integrated national energy models.

Flexibility options can be divided into five main groups, i.e. storage, DR, VRE curtailment, conventional generation, and cross border trade. Instead of analyzing the pros and cons of each option, we are interested to identify key energy modeling issues regarding each flexibility option.

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 requires the diurnal temporal resolution, which can be in different forms such as 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 [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 [59], [60], [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.

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 of Germany suggests that P2X will be a key element for the transition to the 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. investigates 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 is investigated.

There is a huge potential for demand response in the built environment sector 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 represents around 80% of EU average 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.

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].

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 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 for offering flexibility in the power system, as the load can be distributed among a larger group of producers and consumers. For the Dutch context, 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.

Flexibility Options		Key modeling capability
Storage	Daily (e.g. solid state and flow batteries)	HTR
	Seasonal (e.g. pumped-hydro, TES, CAES)	ChO, HTR, P2Heat,
DR	Built environment	HTR, P2Heat, TAB, SC
	Transport	HTR, P2M, V2G
	Industry	HTR, P2G, $P2H_2$, P2L
	Agriculture	HTR, P2Heat, P2L
VRE curtailment and Conventional generation		HTR
Cross border power trade		EEM, HTR

Table 2, Key modeling capabilities for analyzing flexibility options

Abbreviations:
HTR= Hourly Temporal Resolution, ChO= Chronological Order, TAB= Thermally Activated Buildings, SC= Smart Controllers, P2M= Power-to-Mobility, V2G= Vehicle to Grid, P2G= Power-to-Gas, $P2H_2$= Power-to-Hydrogen, P2L= Power-to-Liquids, EEM= European Electricity Market

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.

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% to 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 mechanism in their calculations.

[1] Providing consumers with time-varying electricity rates
[2] Payment to consumers to reduce their load at certain times
[3] Measures to ensure the desired level of security of supply in short-term and long-term.

Uncertainty analysis gets 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 EU final energy demand is satisfied by electricity, while heat consumption and transport account for the rest. Current heating and cooling production in the EU is mainly coming 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. Further electrification of heating, cooling and transport sectors may contribute to GHG reduction, assuming the electricity is generated from renewables rather than fossil fuels [71]. The EU commission suggests electricity as an alternative fuel for urban and suburban driving in its report entitled Clean Power for Transport [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, which are 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) thermochemical process, for example, the reversible Ammonia dissociation process (i.e. $2NH_3=N_2+3H_2$). Xu et. al. [75] provides 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 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 the low-carbon energy system and 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.

New technologies

Development of new technologies makes available additional renewable energy supply sources such as advanced biofuels, blue hydrogen, deep geothermal, wave, and seaweed. It also provides innovative opportunities for further integration of the energy system by implementing P2X technologies, which mainly consist of P2Heat, P2G, $P2H_2$, P2L[1], and P2Mobility technology options. The variable seasonal trend of renewable sources such as 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.

[1] Ammonia, Methanol, and other synthetic fuels (petrol, diesel, kerosene, etc.)

Technological learning

ESMs currently represent technological learning either exogenously or endogenously [82]. Technological change is prevalently expressed in 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 is resulting from a doubling of 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 [85], [86], [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 [89]). MRL differentiates between region-specific technological learning and global technological 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] conclude that the presence of global ETL results in 50% more economically optimal offshore wind capacity by 2050.

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 estimate of the rebound effect magnitude can be challenging [94], while the existence and magnitude 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 are 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 that are not traded in a market. Therefore, it is challenging to clearly disaggregate costs and benefits of infrastructure changes due to energy transition [97]. Long-term investment character of infrastructure 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 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 geographical 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 being transmitted across the consumers. By emerging renewable energy supplies, a new alternative concept of the energy system is being 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, sustainable society, and a competitive energy market. On the other hand, it can increase costs in generation 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 face difficulties answering the decentralized energy system demands. In the 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.

National 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 data preprocessing phase in order to provide spatially resolved data sets for national ESMs. For instance, the global onshore wind energy potential dataset is produced at approximately 1 km resolution [100]. Assuming the availability of the 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 [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 get integrated in 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 recent studies 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 in the decentralized energy system consumers play an active role. An important element of this new system is the role of prosumers i.e. consumers who also produce and share surplus energy generated by renewable energy sources with the grid and/or other consumers in the community [109]. By emerging renewable energies at the microscale, prosumers are not only an important stakeholder of the future smart grids but also may have 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 [112], [113], [114], [115]). In order to grasp an adequate knowledge of the decentralized energy system, the human behavior of the prosumers on energy grid should be considered alongside the techno-economical characteristics (e.g. see [116], [117], [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 make a decision based on their own objective function that may be different from others. Agent-based modeling has been proposed by researchers as a suitable modeling approach for complex socio-technical problems [119] and it is used in modeling the wholesale electricity markets considering human complexities [120]. Ringler et al. provided a review of 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 optimize their own objective function, which can be based on economic (e.g. capital, NPV, and tariffs), technical (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 [122], [123], [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 down 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 which are Top-down, Bottom-up, and Hybrid models.

Top-down (TD) models describe the energy-economy system as a whole and try 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 picture 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 have a 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 detail. 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 [129], [130], [131], [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 is the ability to provide consistent results while considering the three dimensions of energy-economy systems. Model linking (i.e. modeling suite) can include only two dimensions or all the three dimensions. Each of these dimensions can be modeled with a number of different models depending on the complexity of the problem.

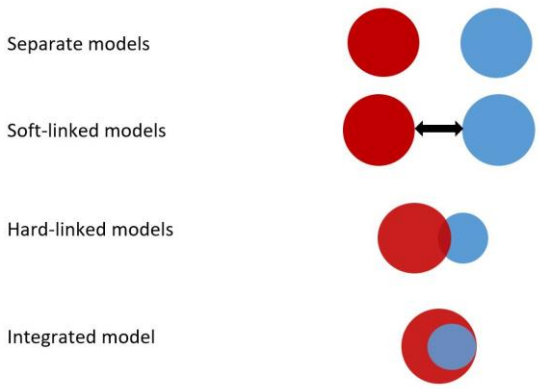

Figure 3, Model linking based on the linking degree
Source: [134]

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 in an integrated model through a unified mathematical approach (e.g. mixed complementarity problems [136]). Similarly, 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.

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 3, Summary of integrated energy modeling challenges and required modeling capabilities

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 are integrated. Moreover, the linking ESMs with TD models capability will be discussed further in Section 5.

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

Capabilities	**Criteria**
• Flexibility options (Storage, DSM, Curtailment, Conventional generation, Cross border trade) • Seasonal Storage (PHES, CAES, TES, HES) • Sectoral coupling technologies (P2Mobility, P2Heat, P2Gas) • 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)	Technological detail and learning
• Fine temporal resolution (HTR, HTR time-slices + CO, HTR time-slices)	Temporal resolution
• Fine spatial resolution (national, regional, GIS)	Spatial resolution
• Human behavior (agent type, neighborhood effect, and heterogeneity)	Social parameters
General capabilities	Modeling methodology
	Data use
	Accessibility and Application

Table 4, The list of assessment criteria based on modeling capabilities and our suggestions

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. However, 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 of the model that are summarized in Table 4 of Section 3.7.

The capability of the model in each criterion is given a score from five (highest) to one (lowest) as presented in Table 5. The importance of each criterion is indicated in Table 7 as the weight of each criterion. 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, these modeling capabilities and the corresponding scores are explained.

Technological detail and learning

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

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 with score one, (ii) time-slice approach with score three, (iii) hourly temporal resolution with score five.

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 regions (e.g. ESME in the UK). Reviewed models are divided in three groups: (i) models without regional depth with score one, (ii) models which consider regions with score four, since it is a considerable improvement, (iii) models which consider GIS data with score five.

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 energy system stakeholders decision making. Models are categorized in two groups: (i) models which capture socio-economic parameters only based on demand curves with score one, (ii) agent-based models which consider a set of decision-making rules for different stakeholders in the energy system with score five.

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 with score one (ii) non-calculator models with score five.

Data use

The depth of technical detail and the quality of 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 be divided into five groups: (i) models which do not indicate their data source with score one, (ii) models which use generalized open-source data with score two, (iii) models which use limited country-specific data with score three, (iv) models which use detailed open-source data with score four, (v) models which use detailed country-specific datasets possibly in combination with global datasets with score five.

Accessibility

Open-access models provide an opportunity for other modelers and experts to test the model and add their insights. With this regard, models are divided into five groups: (i) models which provide no access with score one, (ii) models which provide limited access with score two, (iii) models which are commercial with score three, (iv) models which are open-source but need permission with score four, (v) models which are completely open-source and accessible through web with score five.

Application

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

Criteria	*Score*				
	1	2	3	4	5
Technological detail and learning	No flexibility option and No technological learning		Flexibility options or technological learning		Flexibility options and technological learning
Temporal resolution	More than a year		Hourly time-slices		Hourly temporal resolution
Spatial resolution	Without regional depth			Considering regions	Considering GIS data
Social parameters	Demand curves				ABMs
Modeling methodology	Calculator				Non-calculator
Data source	No data	Generalized open-source global data	Limited country-specific data	Detailed open-source global data	Detailed country-specific datasets possibly in combination with global datasets
Accessibility	No access	Limited access	Commercial	Open-source upon request	Open-source and accessible through web
Application	No publication	Applied in one country	Applied in two countries	Applied across EU countries	Applied globally

Table 5, Summary of the corresponding scores to modeling capabilities in each criteria

Table 6 demonstrates the MCA analysis table with equal weight for all criteria. Right to the score of each model for each criterion, the weighted percentage of that criteria 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.

$$Weighted\ percentage_{(Model,Criterion)} = \frac{Score_{(Model,Criterion)} \times Weight_{(Model,Criterion)}}{\sum_{c=1}^{c=8}\left(Score_{(Model,c)} \times Weight_{(Model,c)}\right)}$$

Equation 1, The formula for calculating the weighted percentage of each (Model, Criterion)

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%	4	13%	4	13%	3.88
ENSYSI	5	17%	3	10%	5	17%	1	3%	5	17%	5	17%	4	14%	1	3%	3.63
OSeMOSYS	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
ESME	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%	1	5%	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	11%	2.25
DynEMo	1	6%	3	18%	5	29%	1	6%	1	6%	1	6%	2	12%	3	18%	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 6, The MCA analysis table with equal weights

PRIMES gets a high score 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 models are not reflected in this table. For instance, METIS works complementary to long-term ESMs as it only simulates a 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.

Sensitivity analysis

Addressing all the policy-induced challenges of the energy system requires a comprehensive ESM that is not available currently. Therefore, a compromise should be made based on the challenges that the model is designed to address. Based on this compromise, a weighted decision matrix can be formed. Here the challenges are divided into two main groups, which are first: intermittency, flexibility, and further electrification; and second: human behavior and decentralization. The first group of challenges puts emphasis on technological detail, high temporal and spatial resolution; while the second group of challenges emphasizes on inclusion of social parameters and high spatial resolution. Table 7 summarizes an example list of challenges and corresponding weights. The importance of each criterion in addressing challenges is weighted from five (highest) to one (lowest). It should be noted that these weights are entirely subjective, thus, the reader can make his own decision tables based on different weights.

Challenges	Modeling methodology	Technological detail	Temporal resolution	Spatial resolution	Social parameters	Data source	Accessibility	Application
Intermittency, flexibility, and further electrification	3	5	5	5	1	3	1	1
Human behavior and decentralization	3	3	3	5	5	3	1	1

Table 7, The weight table of two groups of challenges for the MCA

Using Table 7 for updating the MCA analysis table will lead to a slightly different result which is presented in Table 8. 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 perspective weights, four models stay at the top of the MCA table which are REMix, PRIMES, METIS, and the MARKAL family models. These models demonstrate high scores in nearly all criteria, while a low score in one criterion (for instance, lack of social parameters in REMix) is compensated with a high score in another criteria (in this case, high temporal and spatial resolution). These four models are developed recently (e.g. REMix and METIS) or they are under constant development (e.g. MARKAL family and PRIMES). It shows the trend of integrated energy system modeling points towards the models with improved capabilities in all criteria.

Other models stay at the nearly same ranking position except for IWES, ENSYSI, and EnergyPLAN, which change their position considerably (i.e. more than two steps change). This position change can be explained by the asymmetry in 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.

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

Table 8, Changes in the MCA analysis table based on perspective weights

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 answer future modeling challenges. In the next section, based on our observation from the current state, we discuss two potential modeling solutions to answer future energy system modeling challenges. These solutions are expanding single models and/or linking different models.

5. Developing and Linking models

It is not a practical conclusion 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 of the energy-economy system. Such analysis can be conducted either by developing single models or combining different models (i.e. soft-linking, hard-linking, or integrating).

5.1. Developing single models

Current single models can be developed and/or extended by incorporating further capabilities up to acceptable computational limits. Considering the limitations, the modeler makes choices and/or trade-offs on extensions to the model. Developing a single model that can cover all the mentioned gaps would face limitations, such as complicated mathematical methodology and limited computational capacities (except generic limitations such as high data needs and lack of transparency).

Some common energy system modeling methodologies are optimization, simulation, accounting, multi-agent, and equilibrium. Each mathematical methodology is developed to answer specific energy modeling questions. Integrating two different methodologies can be mathematically very complicated (e.g. Mixed Complementarity Problems in which the optimization and equilibrium formulations are mixed) or not feasible (e.g. mixing Optimization and Simulation formulations). Therefore, single ESMs are naturally limited by their underlying methodology.

One of the main limitations for improving the temporal and geographical resolution of ESMs is the computational capacity. The computational limitation can be addressed either by hardware or software development. Hardware development follows an exponential growth and relates to improvements in the number of transistors, clock frequency, and power consumption of processors. Gils et al. divided software methods to improve computing times of linear optimization ESMs into solver-related and model-specific methods [139]. Solver-related methods focus on improving the solving methodology by using different off-the-shelf algorithms, such as LINDO, CPLEX, GURUBI, and MOSEK, or by practicing customized algorithms, such as Bender's decomposition[1] and parallelization[2]. Model-specific methods relate to heuristic methods, such as clustering, model reduction, decomposition, and parallelization.

[1] A method to decompose a very large Linear Program into smaller solvable LP and NLP [232].
[2] A method to divide a large program into smaller programs and solving all of them at the same time.

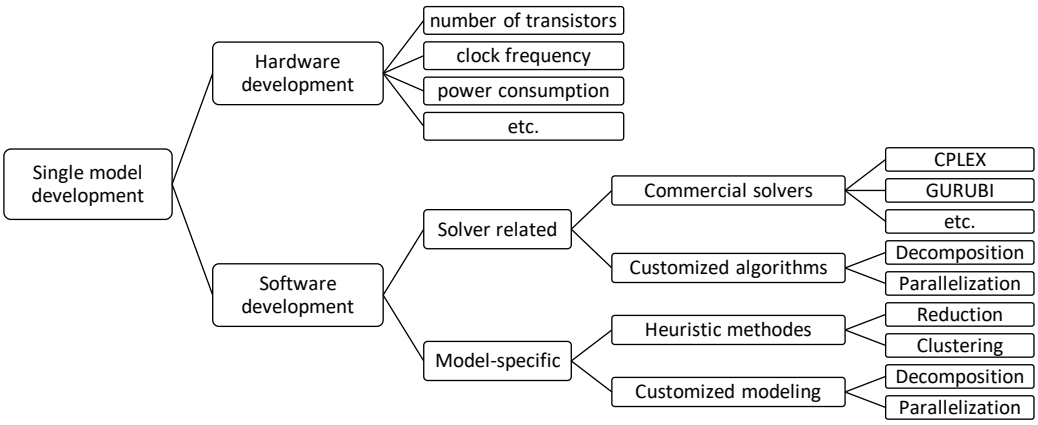

Figure 4, Single model development approaches

Source: [139]

Hardware-related developments proceed at a specific pace that usually is not affected by energy system modelers as users. Solver-related developments are followed by a few energy system modelers (e.g. see the BEAM-ME project [184]), while the rest of the energy system modeling community follows model reduction and clustering methods that can be applied on temporal resolution, spatial resolution, and technological detail (e.g. see [185]). Depending on the research questions to be answered, energy system modelers reduce or coarsen the resolution of the model in order to provide an answer in an adequate timeframe. Therefore, the modeler should make a trade-off between different modeling capabilities by making smart assumptions.

5.2. Linking models

An alternative approach to overcome the limitations of single model development is to form a modeling suite by combining different models. 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 linked 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 identification of connection points in soft-linking (e.g. see [140]), convergent solution in soft-linking (e.g. see [141]), and mathematical formulation for integrated linking (e.g. see [142], [143]). Collins et al. have provided a comprehensive overview of different energy model linking practices and their advantages, limitations, and applicability [144]. 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.

A linking approach is proposed for addressing current energy system modeling gaps. Table 9 provides an overview of identified energy modeling gaps and corresponding linking suggestions. These suggestions 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).

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.	
Lack of endogenous technological learning rates.	
Lack of hourly temporal resolution for capturing intermittent renewables and corresponding potentials.	
Lack of regional spatial resolution for analyzing energy flows between regions across a country.	Hard-linking ESM with a **Regional Energy System Model (RESM)** that involves resolved spatial resolution, land use analysis, and infrastructure analysis
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.	Developing an ABM simulation **Socio-Technical Energy Model (STESM)** that involves stakeholders' behavior, local and neighborhood effects, bounded rationality, and perceived environmental values.
High dependence of ESMs on consumer load profiles.	
Lack of national energy modeling consistency with a European (or an international) energy market.	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 energy modeling consistency with macroeconomic indicators	Soft-linking ESM with a **Macroeconomic Model (MEM)** such as a Computable General Equilibrium (CGE) model that involves the whole economy

Table 9, Model development and model linking suggestions based on the identified energy modeling gaps

The suggestions in Table 9 can be framed in two separate modeling suites based on the methodology of the core ESM. The first modeling suite can be formed around an Optimization ESM (OESM) that provides the cost-optimal state of the energy system assuming a fully rational central social welfare planner. The second modeling suite uses a Socio-Technical ESM (STESM) that demonstrates a more realistic state of the energy system by assuming profit maximizer agents who consider social decision-making parameters, such as behavioral economics, bounded rationality, neighborhood effect, and technology diffusion curve, in their decision-making process.

A: The core ESM

The core component of the suggested modeling suite is the presence 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 standalone analysis is based on specific scenario assumptions such as 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 (that is symbolically demonstrated in Figure 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 elaborate on the role of each policy parameter on reaching to the optimal state of the energy system considering policy targets.

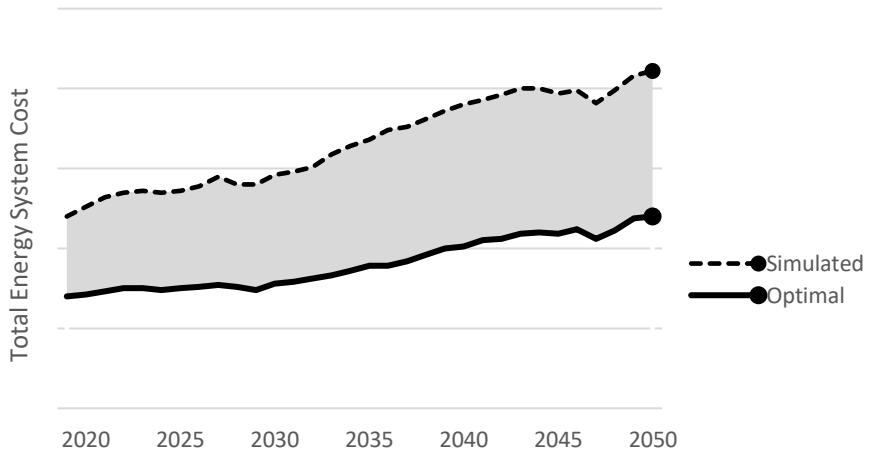

Figure 5, The symbolic gap between the results of the simulation and optimization methodologies.

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 mainly due to their fine temporal resolution and ample technological detail. Agent-based simulation ESMs are not as common as optimization ESMs; therefore, only ENSYSI and PRIMES can be selected from the reviewed models as simulation core ESMs.

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 [145] and GISA SOL [146] provide geographically resolved energy system analysis, they lack the interaction with other regions of the country. As the regional variations of the energy system can have drastic effects on the energy system, it is suggested to hard-link the regional model into the core ESM. Improving the geographical resolution of ESMs can be done in different ways depending on 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. provide a framework to integrate them into an ESM (i.e. the OPERA model) [147]. Focusing on infrastructure, Van den Broek et al. cluster the CO_2 source regions using the ArcGIS software and then incorporate the spatially resolved data into the MARKAL-NL-UU as the optimization-based ESM [148].

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 use the soft-linking approach (e.g. see [149], [150]). 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 to a “fair” estimate of the energy, particularly electricity, import and export flows.

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.

D: Soft-linking with a macroeconomic model

This loop incorporates a macroeconomic model, which keeps demand and supply of commodities in equilibrium based on the statistical economic data such as the supply and demand of commodities, capital stocks and investments, demographics, labor market, and trade and taxes tables. The ESM outputs such as energy prices, energy mix, and emissions are fed into the MEM to update the supply and demand and price tables 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 one time or it can continue until the results reach a convergence criterion, which is a user-defined criterion that determines the maximum gap between 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 [151]). The SESM analyzes the social aspects of the energy systems such as stakeholders’ behavior, bounded rationality, imperfect communication, and environmental perceived value.

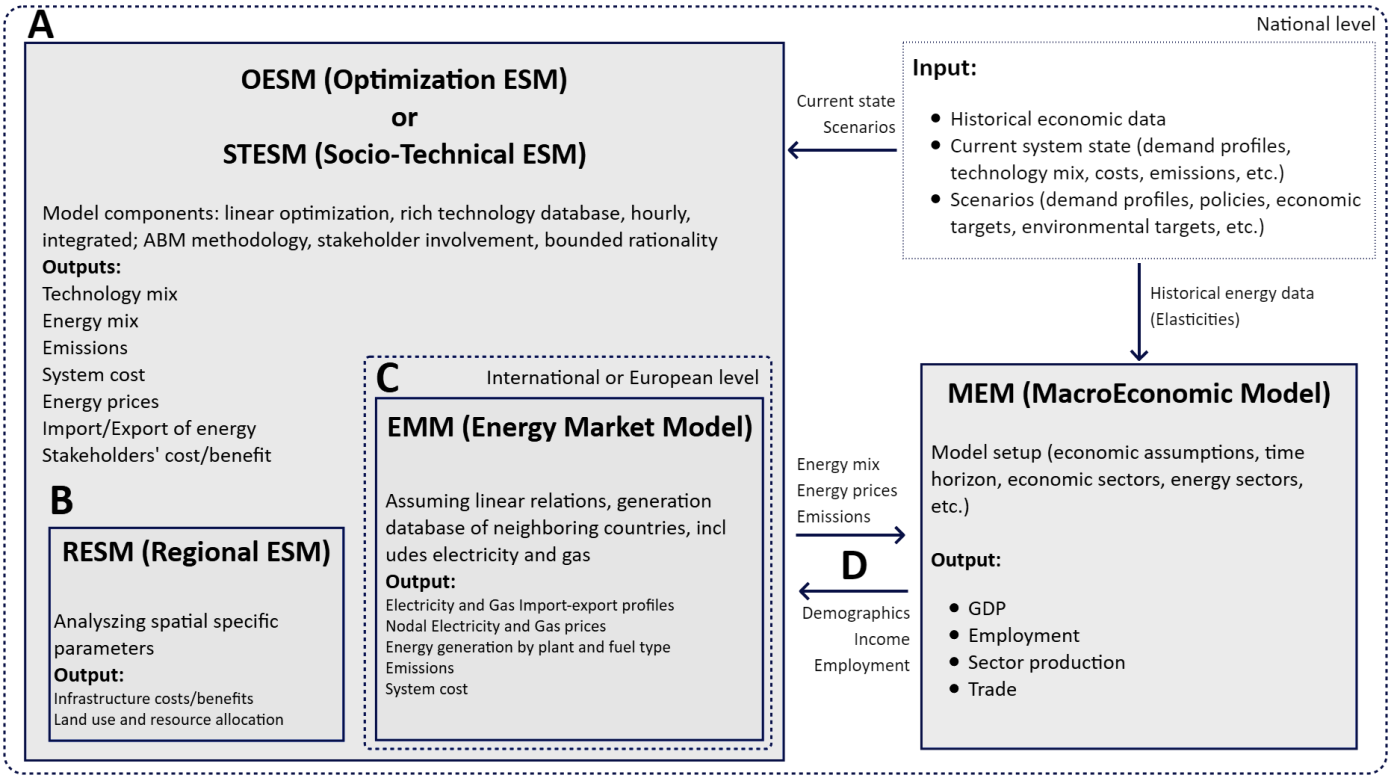

Figure 6, Optimization-based or Simulation-based conceptual model linking framework for the low-carbon energy system modeling suite

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.

A limitation of this study is that all the information about models has been gathered from officially published documents, which may get outdated quickly as the models are constantly under development. Therefore, this review provides rather a static view on ESMs. Only a limited number of energy system models were presented in this review, which is mainly due to limited time, resources, and access to modeling databases. There can be other challenges regarding the modeling of low-carbon energy systems that were not covered explicitly in this study. Some examples 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 use of multi-criteria analysis, in which scores are subjectively assigned, although a clear explanation is 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 modeling suites.

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Appendix A. Summary of integrated energy system modeling tools

1. Introduction

Due to their complex nature, energy models can be categorized in many different ways. To differentiate energy models, J.C. Hourcade [152] suggested three major contexts, which are Purposes, Structure, and Input assumptions. Later on, van Beeck [153] expanded his work by keeping Purpose and Input assumptions of the model and enlarging Structure context into several perspectives, including the analytical approach, underlying methodology, mathematical approach, geographical coverage, sectoral coverage, time horizon, and data requirements. Recently, Laha and Chakraborty [154] conducted a comprehensive review of different energy system modelling classifications including eight categories: (i) the purpose of constructing the energy model, (ii) the analytical method employed for the model, (iii) the methodology incorporated while designing these models, (iv) the mathematical approach implemented, (v) the topographical area the energy model covers, (vi) the sector(s) for which the energy model has been constructed specifically for, (vii) the time frame of the energy model analysis, and (viii) the type of data required (Figure A - 1).

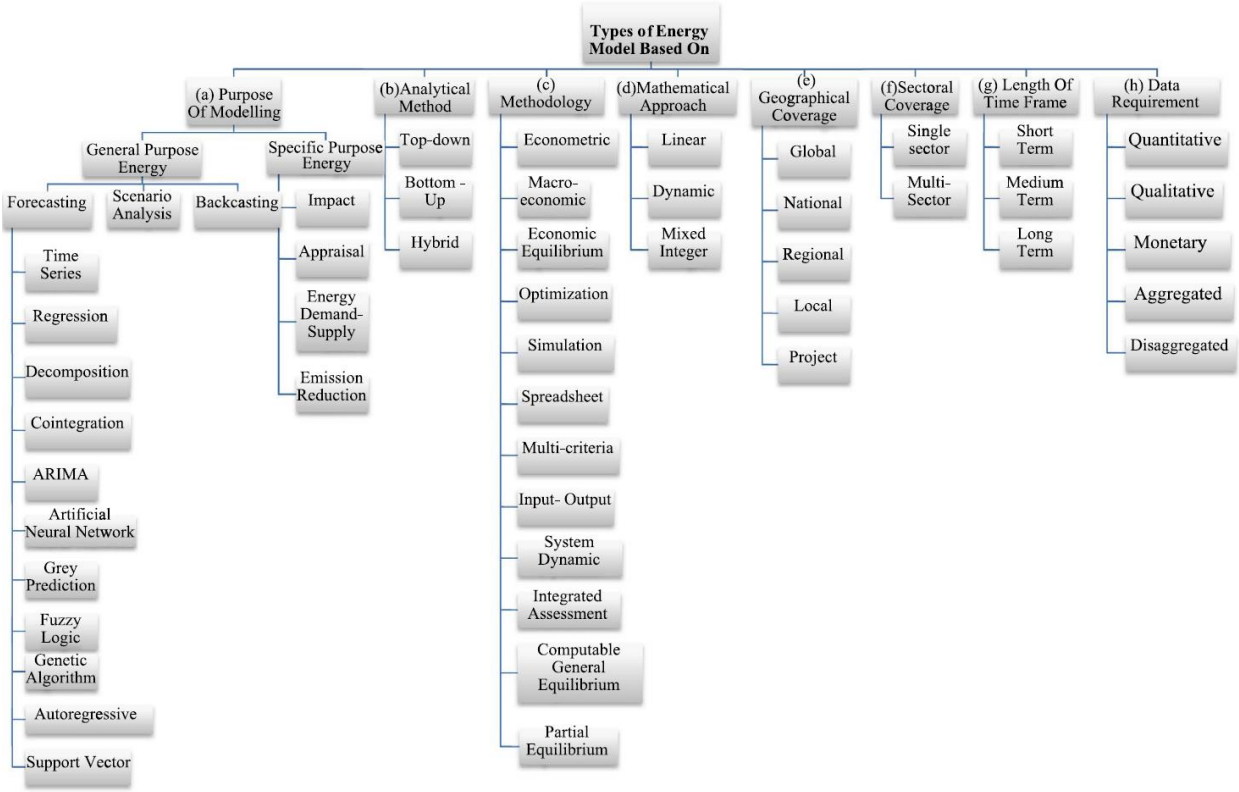

Figure A - 1, Energy models may be classified in different ways.

Source: Laha and Chakraborty [154]

A recent review compares several energy system models in the UK and highlights the wide diversity of models and the predominant features of them [4]. Moreover, Connolly et al. [2] have listed a complete specification of different energy modeling tools. According to these reviews and the author's literature review, integrated energy models with national coverage are listed. In the following, the description of each model and its properties are summarized.

The aim of this section is providing an overview of integrated energy system models. All the models in this review share these two characteristics. First, they are/have been used at the national level. Second, they cover all three energy sectors, namely, Electricity, Transport, and Heat. In each section, a brief history of the model alongside some features and downsides are provided. For further information regarding each model, readers are encouraged to follow the respective references.

2. DynEMo

Developed by University College London, this dynamic energy model simulates the whole energy system at the national level. The model considers electricity (renewable included), oil, coal, gas, and biomass and interconnections between these energy carriers. On the demand side, four sectors play a role, which are dwellings, services, industry, and transport. The system starts with initial conditions, for example, initial demand (supply) profile at time zero. Then the simulation runs and calculates the demand (supply) in the nest time-step that can be a minute later. In each time-step, a control system gets the information from sensors, processes the information and improvises a strategy, then implies the system-wide strategy for the next time-step.

The aim of this model is to demonstrate the behavior of all the main elements of the energy system, including both people and technologies. Consequently, the modeling of any individual element, like heat pump performance, is simplified [18].

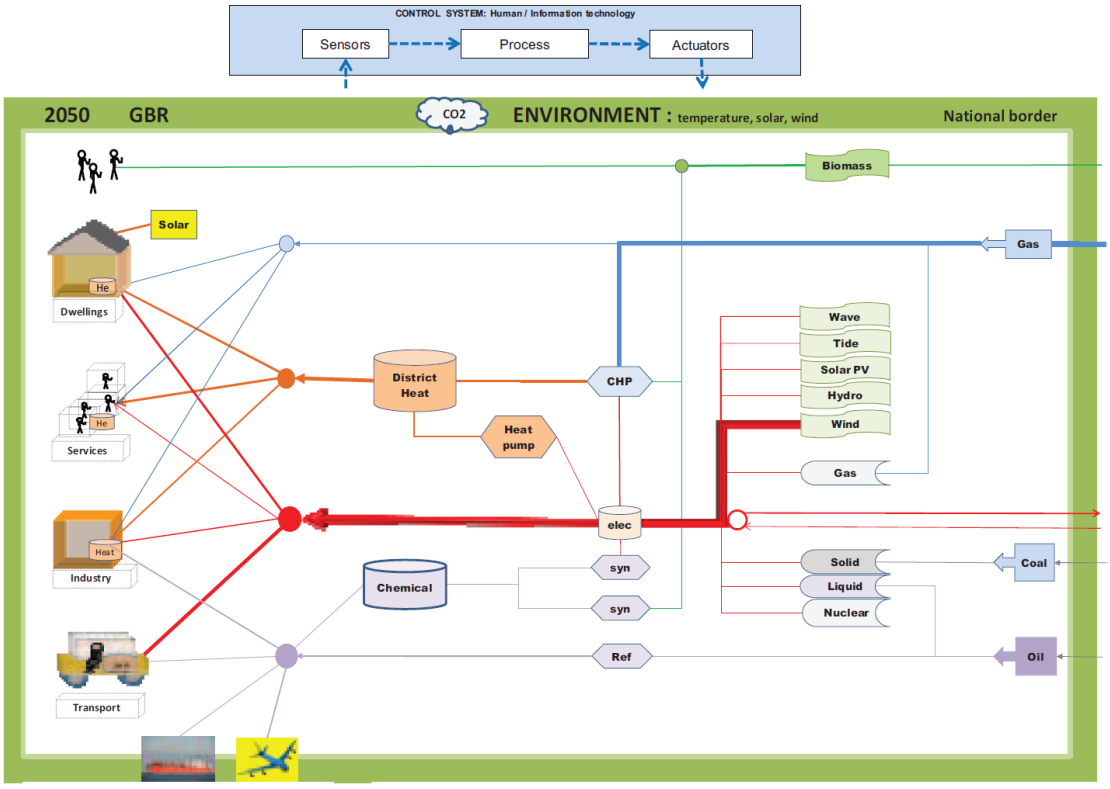

Figure A - 2, Principal components of the DynEMo energy system model

Source: [19]

The model follows a dynamic bottom-up approach with the basic calculation of energy elements. It shows the basic dynamic relation between energy subsystems in different time-steps. However, it faces significant challenges in national energy boundaries, like optimization of international electricity trade. Moreover, it does not account for recently developed energy storage possibilities, like hydrogen.

3. E4cast

Designed specifically for the Australian energy sector, E4cast is a dynamic partial equilibrium model that contains domestic electricity and gas sectors. It is used to project energy consumption by fuel type, by industry and by state or territory, on an annual basis [21]. Its first version was documented in 2001 and it has been under development since then. In the latest documented version, the model comprises 19 primary and secondary fuels. A detailed demand profile based on income, fuel prices, and efficiency is provided for each fuel. The model bases its assumptions according to Australian Energy Statistics.

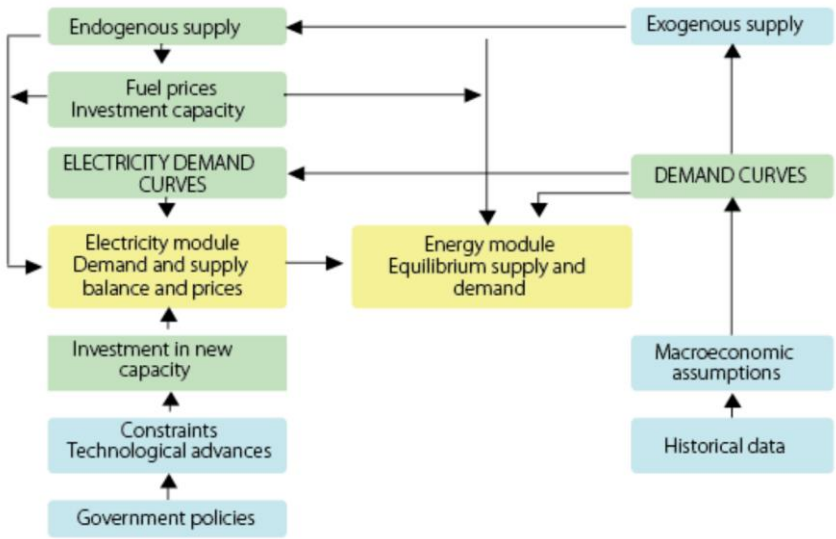

Figure A - 3, E4Cast energy model with the aim to forecast the future Australian energy sector

Source: [21]

4. EnergyPLAN

Started from 1999, this model first was written in the Excel spreadsheet and from that time it was under modification and development with more than thirteen versions. The most recent version, which is owned by Aalborg University, was reviewed in September 2017 [23]. EnergyPLAN is developed by the Sustainable Energy Planning Research Group at Aalborg University, Denmark. This bottom-up model optimizes the energy system by running two different analyses, either a technical or a market-economic calculation. After an initialization of the model, the user can choose which type of optimization is needed. The technical calculation aims to identify the least fuel-consuming solution based on the Wh consumption of electricity and heat, while the market-economic calculation seeks the least-cost solution of the energy system based on the energy price per Wh. The model assumes hourly market equilibrium and determines the energy market price respectively.

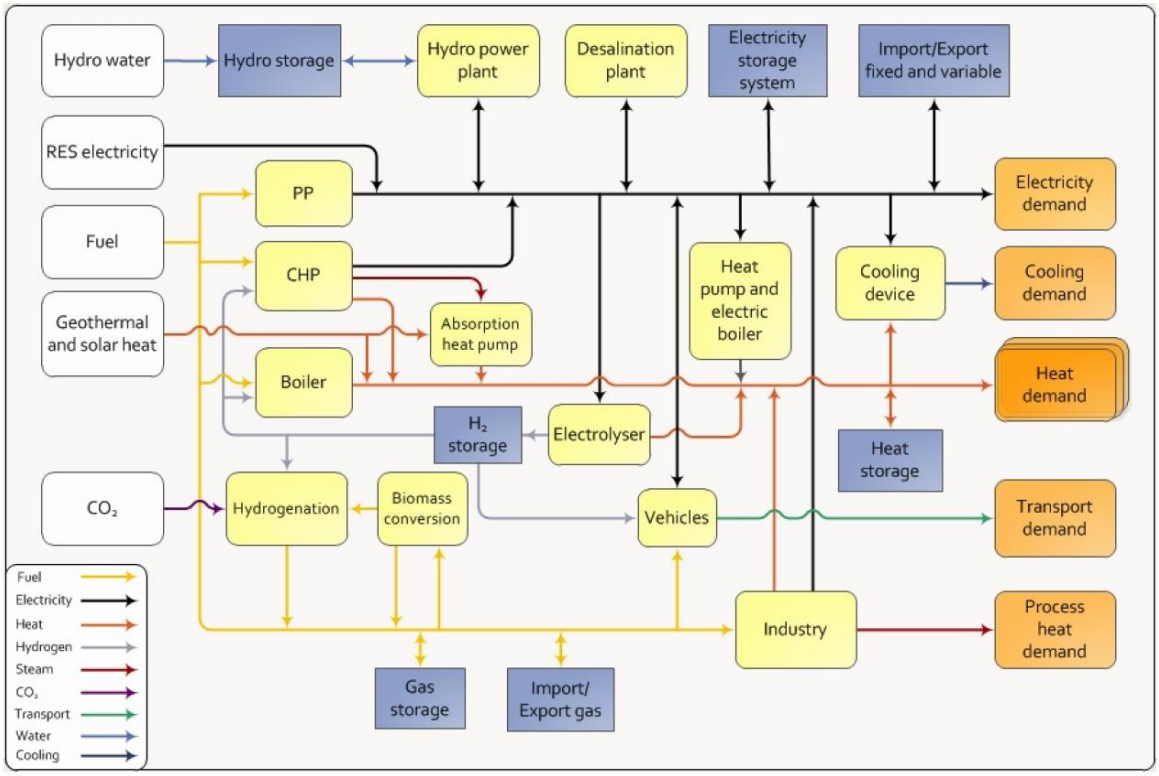

Figure A - 4, The whole energy system modeled by EnergyPLAN

Source: [23]

The model has an hourly time resolution, thus it is able to capture renewable energy integration in the whole energy system in accordance with storage possibilities. Moreover, the model supports recent technology developments like hydrogen storage option.

5. ENSYSI

The **En**ergy **Sy**stem **Si**mulation model is designed by PBL in the Netherlands. This agent-based model (ABM) simulates the energy system from 2010 to 2050 in yearly time-steps. The demand and supply of energy carriers are matched in each time-step, except electricity, in which the matching occurs on an hourly basis in order to simulate the electricity market. At the end of each time-step, actors (large or small companies, house owners, farmers, etc.) make investment decisions. The investment decisions depend on different parameters such as the cost of technology, the investment cost, CO2 reduction targets, actors' social behavior, and the complication of the technology [25]. Moreover, not all actors give the same weight to investment parameters. In order to capture different behavioral decision-making outcomes, each group of actors is composed of different actor types such as innovators, early adopters, majority, and laggards. The output from each time-step is fed into the next time-step as the initial condition, and the simulation runs yearly until the end of the time frame.

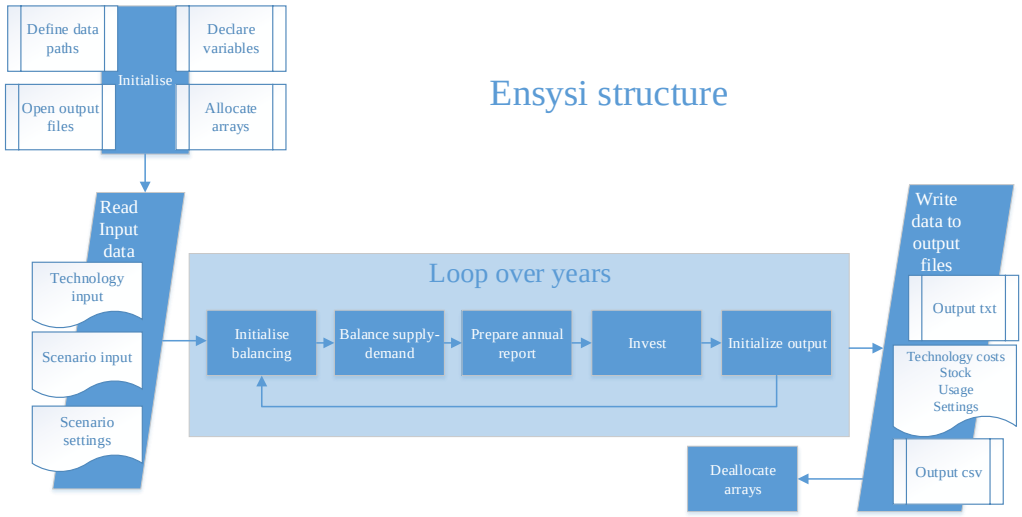

Figure A - 5, The structure of the ENSYSI simulation model

Source: [25]

Designed in 2013, ENSYSI is a relatively young model with no formal application. The model code is written in the Fortran95 programming language with input and output files in ASCII text format. The model comprises +280 technologies and +40 energy carriers (e.g. crude oil, vegetable oil, residual oil, waste oil, etc.). One simulation run of the 2010-2050 period takes a few minutes on a laptop PC.

6. ESME

This bottom-up model has been developed by ETI in the UK. Its aim is to find an optimized long-term pathway while meeting emission targets and other user-defined constraints. Although this model covers the whole energy system, it has relatively limited detail in technology modeling, compared to individual technology models. Although it is a pathway optimization model like TIMES/MARKAL, ESME undertakes a Monte Carlo analysis in its core, unlike them. ESME is a policy-neutral tool, therefore, taxes, subsidies, and other economic policies are absent in this model [27].

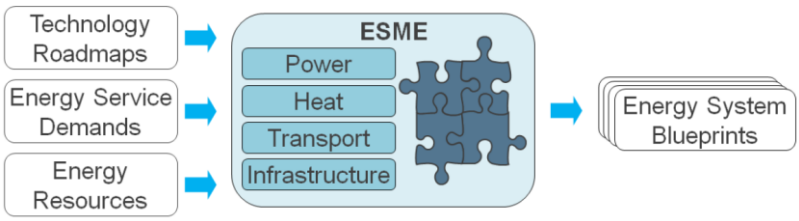

Figure A - 6, A schematic diagram of the ESME model, which optimizes the policy-neutral energy system in the long-term

Source: [27]

An interesting feature of the ESME model is its connection with other ETI developed models. As shown by Figure A - 7, together with other detailed technological models, ETI proposes a framework for the whole energy system modeling. However, ESME lacks a link with a general economic model.

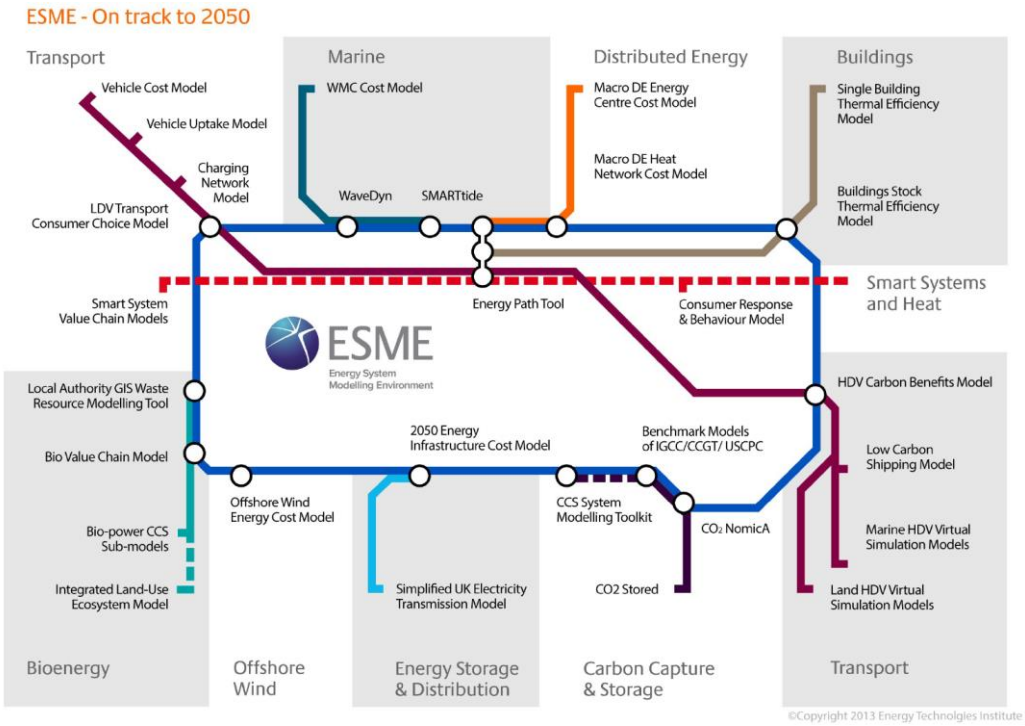

Figure A - 7, A schematic map of the ESME model in relation with other ETI projects

Source: [27]

7. ETM

The Energy Transition Model (ETM) is an online simulation model developed by Quintel Intelligence [29] for assessing possible future scenarios mainly in the Netherlands. Its relatively user-friendly interface makes it a suitable tool for policymakers and other non-technical stakeholders to execute their scenarios and track the results. Moreover, the model's source code is available on GitHub for open-source developments.

The model matches electricity demand and supply according to the merit order functionality. The merit order ranks the power plants based on their marginal costs. Those plants with lower marginal costs are dispatched first to meet the demand. The flexibility options are divided into three subcategories: storage (electric batteries), conversion (power to hydrogen/gas), and demand response. All flexibility technologies are ranked by the user and the model trivially allocates the excess electricity to the first technology (e.g. EVs storage) until its maximum capacity is reached and then goes to the next option. The model lacks any explicit macroeconomic formulation or feedbacks.

8. IKARUS

Developed by the former German Federal Ministry for Education, Science, Research and Technology (BMFT), IKARUS aims to model the energy system of the Federal Republic of Germany. This bottom-up linear optimization energy model uses a dynamic 5-year time-step to calculate the optimized system cost [31]. The model consists of ten major sectors (primary energy, electricity, district heat, refinery, gas, coal conversion, industry, transportation, small consumer, household), where each sector is divided into subsectors (Figure A - 8).

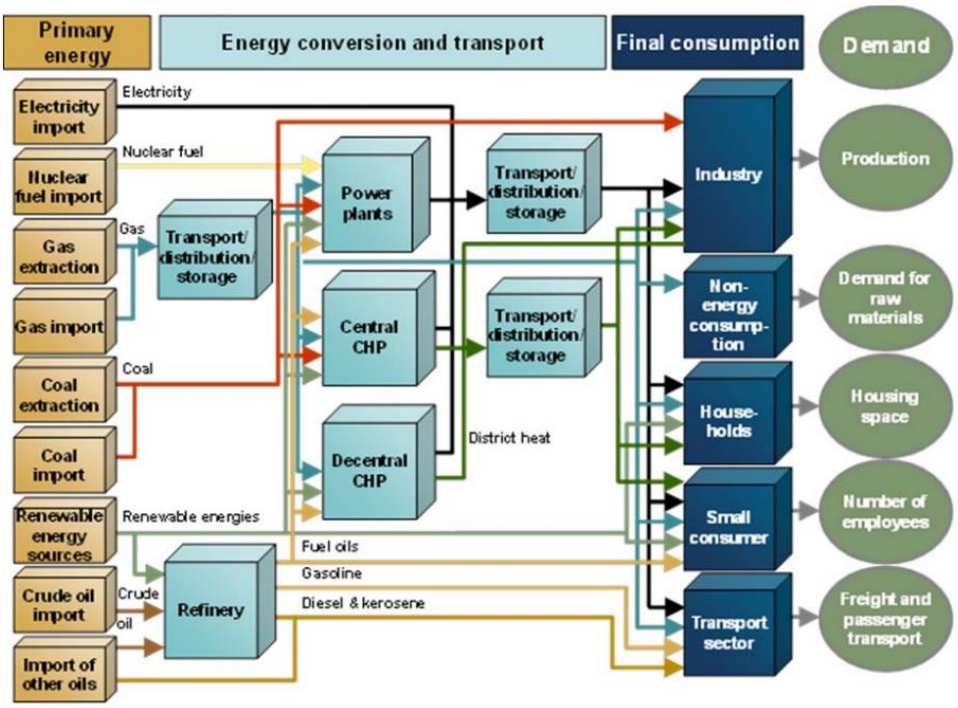

Figure A - 8, The structure of the IKARUS energy system model used for the Federal Republic of Germany

Source: [32]

IKARUS was developed to model the German energy system, including investigations such as the role of CCS in carbon emission reduction [155], the effects of stochastic energy prices on long-term energy scenarios [156], or using fuzzy constraints to obtain a better representation of political decision processes [157].

9. IWES

Integrated Whole-Energy System (IWES) is an optimization model developed by the Imperial College London in order to analyze the decarbonization pathways of the UK energy system. It is an improved version of the Whole Electricity System Investment Model (WeSIM) [158] that includes hydrogen infrastructure and heat technologies such as district heating, heat pumps, etc. This model minimizes the total cost of long-term infrastructure investment and short-term operating cost while considering the flexibility provided by different technologies and advanced demand control [34]. Energy system flexibility is analyzed comprehensively by including intersectoral analysis at hourly temporal resolution.

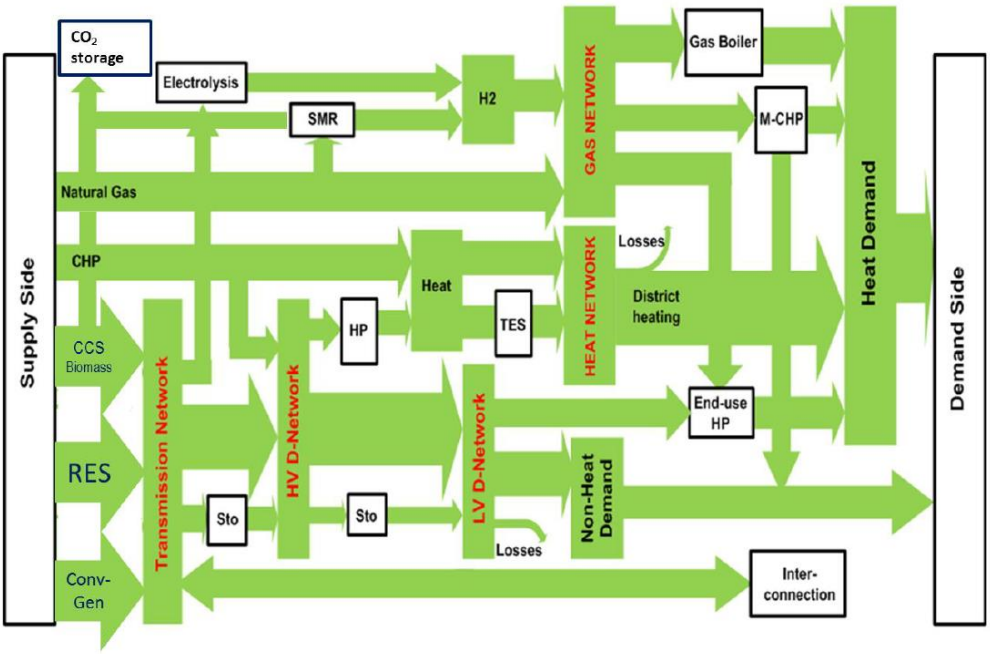

Figure A - 9, The schematic of the IWES integrated energy model

Source: [34]

10.LEAP

Being developed at the Stockholm Environment Institute, USA, LEAP is a simulation model that is used mainly for long-term energy scenario analysis. Therefore, most of the calculations in the model occur on yearly time-steps. However, electricity calculations can be done in user-defined time slices during the year. LEAP supports a wide range of different modeling methodologies from bottom-up, end-use accounting techniques to top-down macroeconomic modeling. It is an integrated modeling tool that can be used to track energy consumption, production and resource extraction in all sectors of an economy [159].

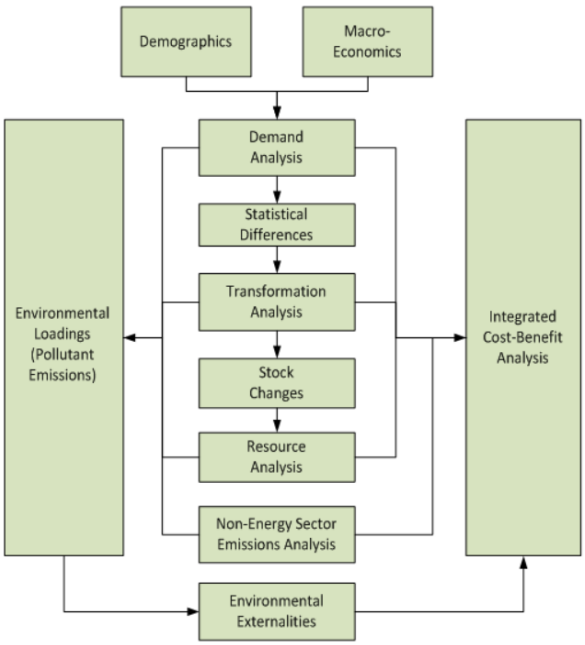

Figure A - 10, The Structure of the LEAP model calculations

Source: [36]

11.MARKAL, MARKAL-MACRO, TIMES

MARKAL (an acronym for MARKet ALlocation) is a mathematical model of the energy system of one or several regions that provides a technology-rich basis for estimating energy dynamics over a multi-period horizon [38]. The aim of the model is to find the least-cost energy supply strategies, considering the whole energy system properties. The model incorporates the partial equilibrium on energy markets, which means suppliers produce exactly the quantities demanded by the consumers. The model considers three seasons with day/night, which equals to six timeslices.

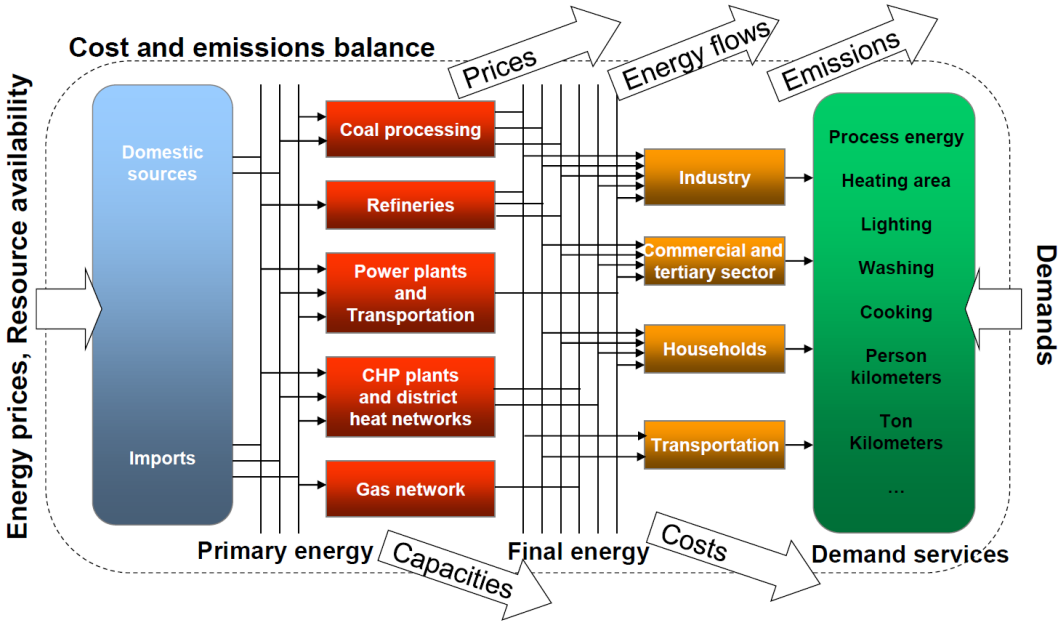

Figure A - 11, The generic TIMES schematic.

Source: [160]

Many models have been born from MARKAL, like MARKAL-MACRO, TIMES, and SAGE. The first one is a general equilibrium model obtained by a combination of the MARKAL model with macroeconomic equations. TIMES (an acronym for The Integrated MARKAL-EFOM System [39]) embodies the core of the MARKAL model with few improvements such as variable length time periods, flexible time slices, flexible processes, etc. SAGE (an acronym for System for the Analysis of Global Energy Markets [161]) is a time-stepped version of MARKAL where a static partial equilibrium is computed for each time period separately and it is used for global integrated energy and environment analysis [38].

12.METIS

METIS is an optimization-based model that is developed by a consortium (Artelys, IAEW (RWTH Aachen University), ConGas, Frontier Economics) as part of the Horizon 2020 European project. It is owned and operated by DG ENER of the European Commission [20]. It simulates the whole EU energy system on an hourly basis for a year considering uncertainty (weather and other stochastic events).

Its first version was delivered in January 2015, therefore, the model is relatively new. It runs on a commercial Artelys Crystal Platform, intellectual property of Artelys [162]. In order to directly replicate the METIS simulations, the model is supposed to be available for EU member states administration bodies with a limited access. The behavioral assumptions of actors and consumers are implemented exogenously and the model does not capture human factors separately.

13.NEMS

NEMS (National Energy Modelling System) is an energy-economy model used in the United States for the period of 1990-2020. This large-scale equilibrium model, which was designed and used by the Energy Information Administration (EIA), follows a hybrid approach in energy system modeling [163]. NEMS consists of three bottom-up and two top-down modules that interact with the integrating module, which ensures the general equilibrium by iterations. The supply module covers oil and gas, natural gas transmission, coal, and renewable fuels; the demand module comprises residential, commercial, industrial, and transportation demands; and the conversion module involves electricity market and

petroleum market models. The national and international economic parameters are linked with the model via top-down Macroeconomic Activity and International Energy modules. The aim of NEMS is to project the energy, economic, environmental, and security impacts on the United States of alternative energy policies and different assumptions about energy markets [22].

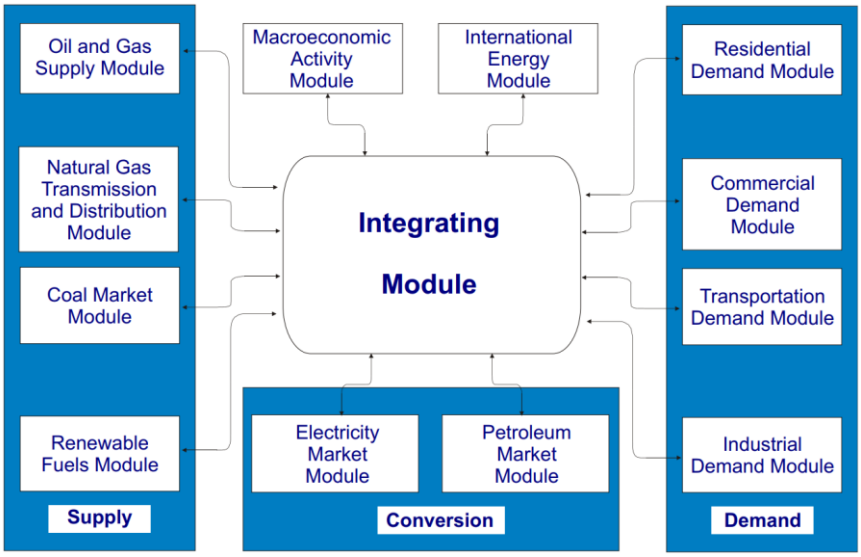

Figure A - 12, The structure of NEMS energy model, which consists of three main bottom-up modules and two top-down modules, all linked to the integrating module

Source: [22]

NEMS is developed for the U.S. energy system so its use is limited for other applications and countries. NEMS is only used by a few organizations outside of the EIA. Users who have requested NEMS in the past have found out that it was too difficult or rigid to use. Moreover, it is poorly suited for application to other countries [164].

14.OPERA

Developed by ECN, OPERA (Option Portfolio for Emissions Reduction Assessment) is an integrated optimization energy system model used for the Netherlands. It determines which configuration and operation of the energy system, considering emission reduction goals and other policy restrictions, meets the energy and environmental needs of the Dutch society [24]. The optimization model uses LP (Linear Programming) approach for minimizing the costs of the system for a specific year in the future [165]. OPERA includes centralized and decentralized electricity and heat energy systems; transmission grid systems for electricity, natural gas, and hydrogen; and storage and flexibility options including CCS, hydrogen, CAES, and EVs. It uses hourly data (e. g. hourly demand and supply profiles). However, in order to reduce the computational workload, the model runs in a limited set of time-slices (i.e. 61 time-slices per year in FLEXNET [166] project).

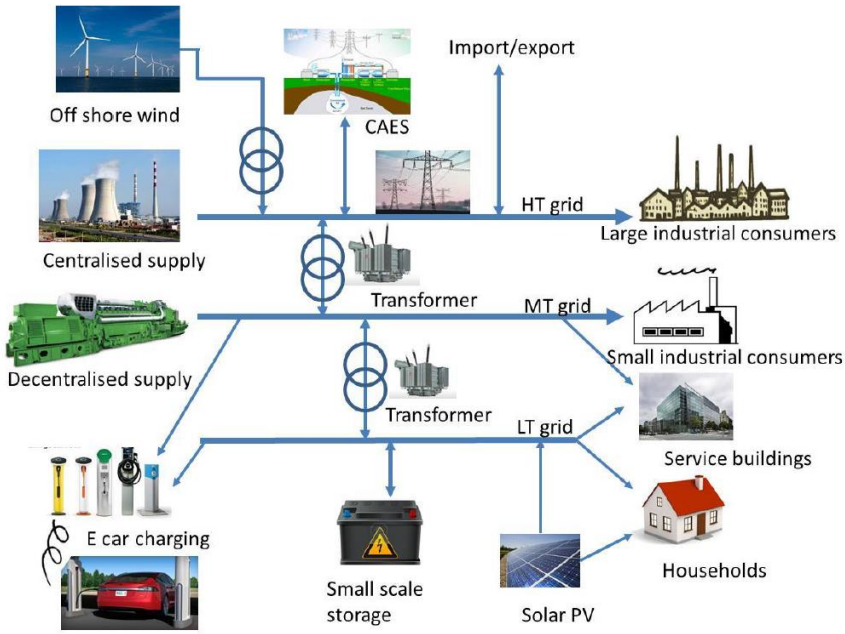

Figure A - 13, An illustration of the electricity grid network modeled in OPERA. The model also includes natural gas, hydrogen, and heat networks

Source: [24]

15.OSeMOSYS

The main novelties of the Open Source Energy Modeling System (OSeMOSYS [167]) is first, its relatively less significant learning curve and time commitment to build/operate and, second, being open source without a need for an upfront financial investment [26]. This optimization model is used for energy system analysis over medium (5 years) and long-term periods. The simple open source structure of the model makes it a proper teaching tool for energy modelers.

The model consists of several blocks that can be modified depending on the application and each block is divided into different abstraction levels. For example, in the objective cost block, the plain English description abstraction level describes the lowest net present cost of the energy system given the energy demand data. Meanwhile, the mathematical box abstraction level describes the algebraic formulation of the block.

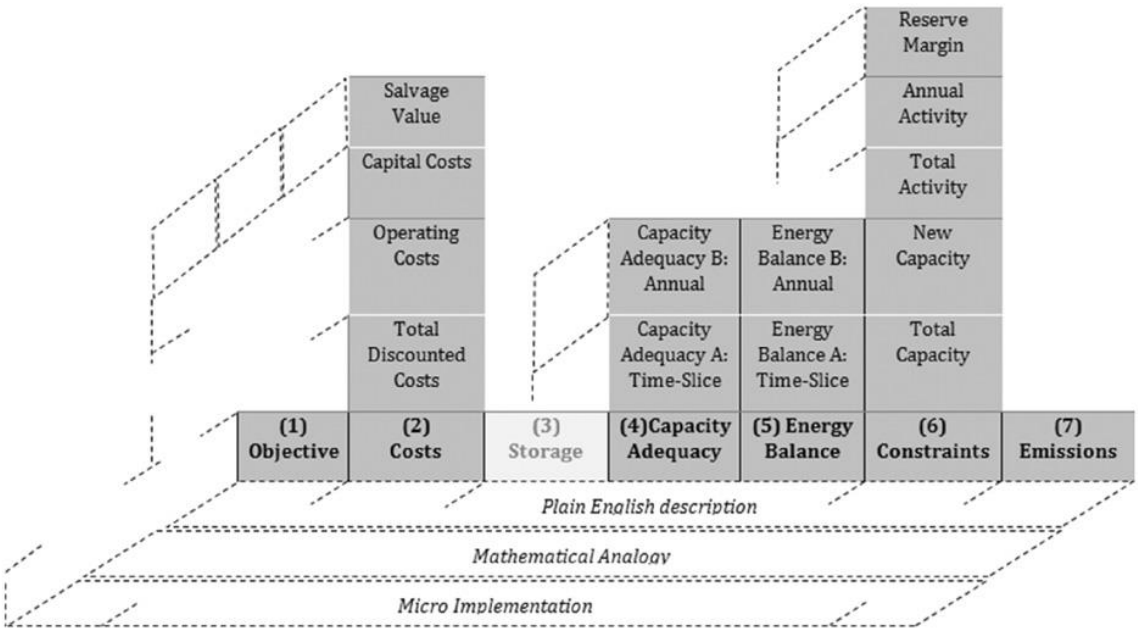

Figure A - 14, The OSeMOSYS model consists of several blocks that can be modified according to the application and each block is divided into different abstraction levels

Source: [26]

16.POLES

The POLES (Prospective Outlook on Long-term Energy System) model has been used as an analytical tool for providing energy scenarios that inform the energy policy development at world, EU, and national levels [28]. It is a recursive simulation partial equilibrium model of the energy system that runs annually. After getting the exogenous assumptions from socio-economic developments and policy conditions, the model matches the supply and demand of energy to reach the market equilibrium in different geographical regions.

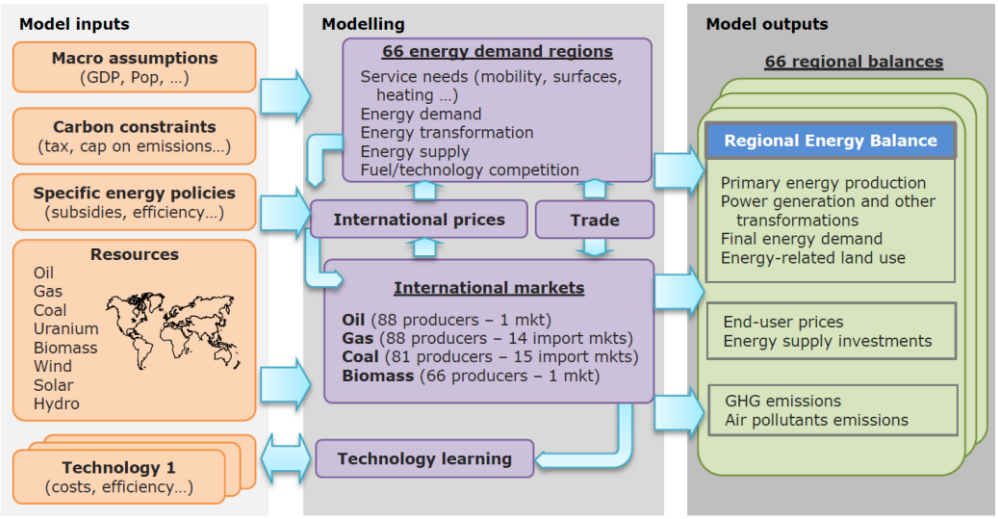

Figure A - 15, A schematic representation of the POLES-JRC model architecture.

Source: [28]

17.PRIMES

The Price-Induced Market Equilibrium System (PRIMES) has been developed by the Energy Economy Environment Laboratory (E3MLab) at the National Technical University of Athens (NTUA) [30]. It consists of several sub-models for expressing the behavior of specific agents (representative household, industry per sector, services, power generation, etc.), supplier (cost minimizer or benefit maximizer) or demander (benefit maximizer) of energy. Then sub-models are connected to each other to ensure the market equilibrium conditions and policy constraints (i.e. emissions restrictions) are met. The final decision is made up economically (based on energy demand and price), although, it includes detailed technological and engineering constraints.

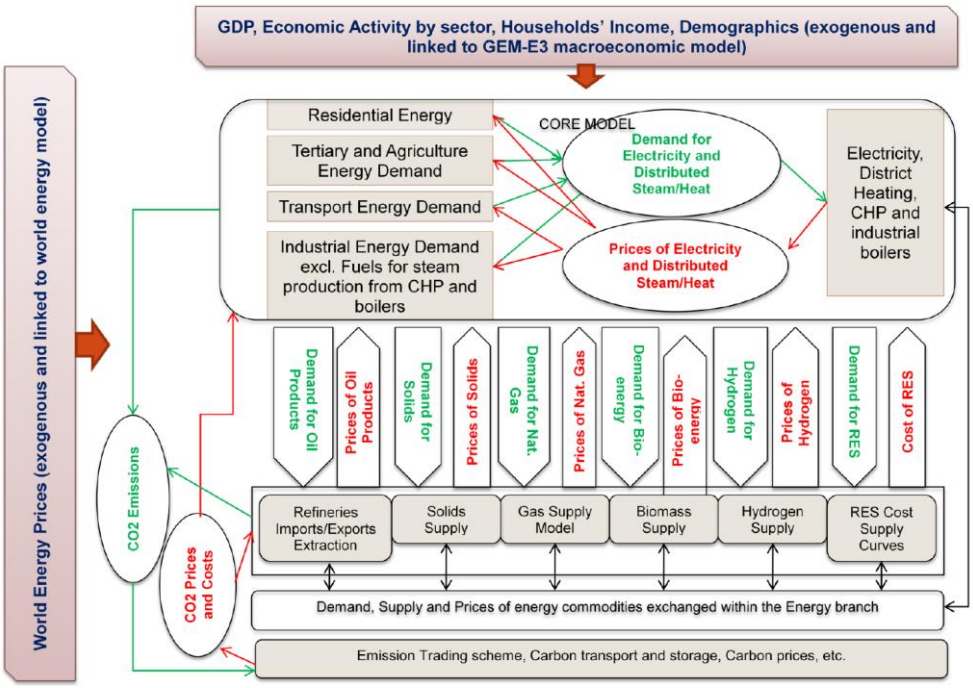

Figure A - 16, The structure of the PRIMES energy model.

Source: [30]

The model runs in five years periods from 1990 to 2050, while it is calibrated to the Eurostat statistics from 2000 to 2010. Agents' behavior in decision making is forward-looking and usually it assumes perfect foresight over short-time/long-time horizons for the demand/supply side of the energy system.

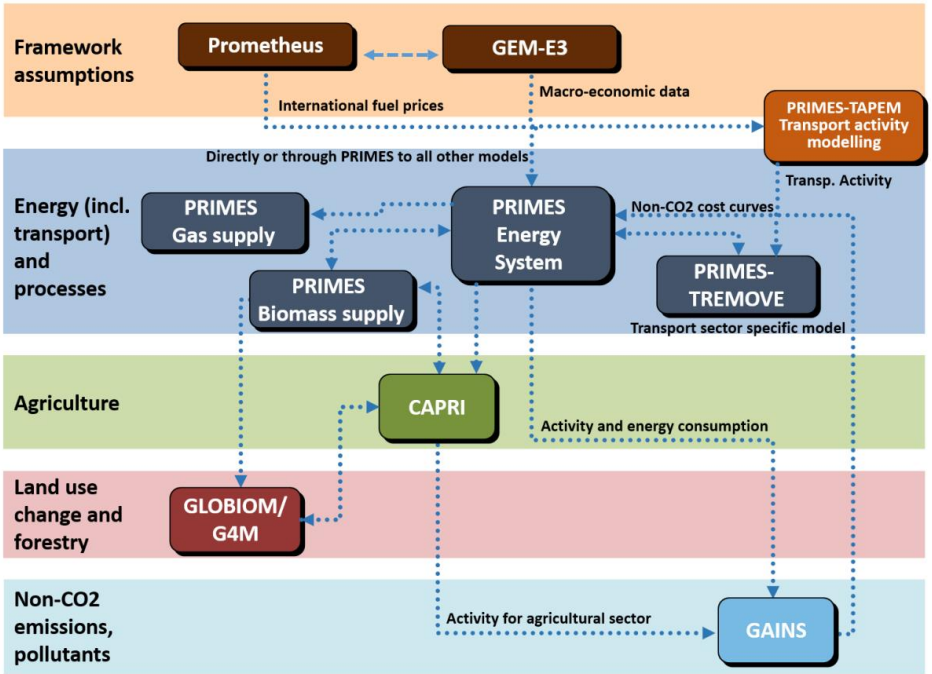

Figure A - 17, The whole European energy system model with the participation of the PRIMES model.

Source: [168]

One of the main advantages of the PRIMES energy model is its modularity and the integration with other energy models. In order to model the EU reference scenario, this core model is in interaction with the GEM-E3 macroeconomics model, the POLES or PROMETHEUS world energy model, the CAPRI agricultural model, the PRIMES-TREMOVE transport model, and the PRIMES Gas supply model.

18.SimREN

This bottom-up simulation energy model was first developed in 1999 by the Institute for Sustainable Solutions and Innovations (ISUSI) in Germany. The model uses detailed weather data in order to optimize the renewable energy supply. The optimization process calculates the installation of power generation capacity based on the highest possible production of electricity from regional renewable sources while maintaining the rules of sustainability [35]. Electricity simulation is done in the intervals of 15-minutes to assure system's reliability in supply. This model has been developed specifically for Japan, but it has been used also to analyze the electricity sector of the Catalonia region of Spain [169].

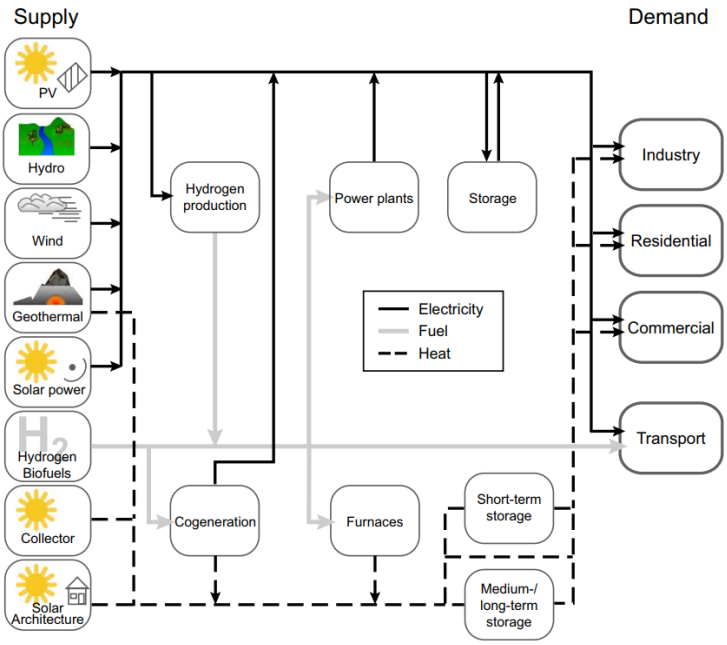

Figure A - 18, The structure of the SimREN energy model in the ERJ (Energy Rich Japan) project.

Source: [35]

19.STREAM

This simulation-based energy model has been developed by DTU and EA Energy Analysis since 2007. STREAM (Sustainable Technology Research and Energy Analysis Model) is not an optimization tool, so it cannot give the optimal and low-cost solutions for the future energy market, but it allows simulating different scenarios and comparing different solutions for the system [37]. It is divided into two sub-models: the Energy Flow model and the Duration Curve model. The energy flow model is a static model that calculates the national energy demand in four sectors (residential, services, industry, and transport) on a yearly basis. The second sub-model optimizes the Danish electricity and district heating systems on an hourly basis. However, this is not a financial optimization but only minimizes the total installed capacity of power and CHP plants.

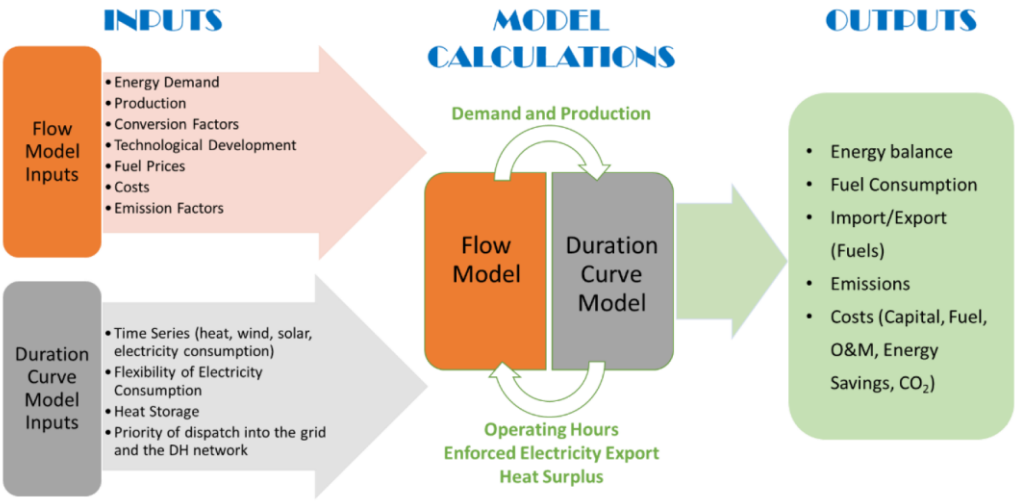

Figure A - 19, The structure of the STREAM energy model.

Source: [37]

The model attempts to monetize all important economic factors. However, some elements are missing in the calculation like externalities from other pollutants than GHG, changes in transport mode, demand response by consumers and industry, and infrastructure costs [170].

20. Recent initiatives in integrated energy modeling

Societies are facing new energy transition challenges that demand energy modeling frameworks to represent not only economic and technical aspects of the energy sector, but also interdependencies between them, environmental impacts, demand response, and international politics. Several researchers are struggling to design a new energy modeling framework that considers these interdependencies as well as intermittent renewable energies.

In this section, an overview of three recent initiatives in integrated energy modeling, notably, Nexus, EMP-E, and EU-Calc, is presented. After providing a short introduction to the developers' team, a summary of the corresponding model is provided.

1. Nexus

The Integrated Energy Systems Modelling Platform (Nexus) is an initiative from the Energy Science Center of ETH Zurich that aims to develop an integrated energy model by combining existing and new tools from different disciplines. The aim of this project is to assess the impact of economical, socio-technical, and political decisions on the future energy system [171].

Crespo del Granado et al. [172] stated that the Nexus modeling platform follows four aims that will:

1- Standardize data and modeling assumptions
2- Jointly represent layers, sectors, and components of the energy system
3- Integrate existing knowledge to facilitate interdisciplinary research
4- Bridging the gap between engineering and economic energy models

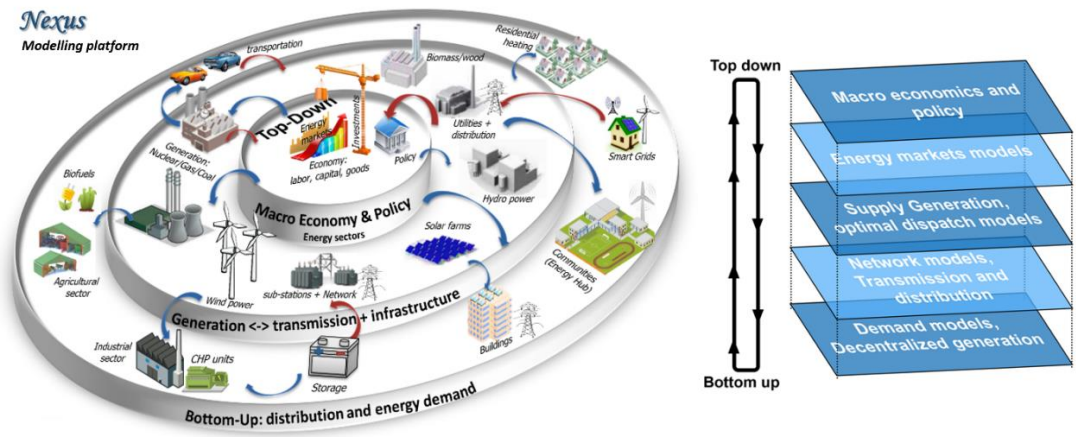

Figure A - 20, The schematic of linking energy sectors and layers of energy modeling approach in the Nexus modeling platform.

Source: [172]

The authors divide energy modeling approaches into three main categories. i.e. top-down, bottom-up, and hybrid approaches. Top-down models like CGE and econometric models are typically used for scenario analysis, but they come with some weaknesses such as high level of sectoral and time aggregation, few detail in power system, not well suited for financial markets, shortage of stochastic elements, and lack of imperfect competition. Bottom-up approaches like MARKAL [173] and TIMES [174] demonstrate a decent level of techno-economic detail, but they lack in considering energy network and decentralized generation sources, feedback relations with the macroeconomic model, and autonomous microeconomic behavior. Hybrid approaches like MESSAGE-MACRO [175] and EPPA [176] try to cover the drawbacks of the other two approaches but still they suffer from the inconsistency in the behavioral assumptions in the models. In general, existing modeling approaches lack at least in one of the following features: “representing interactions with decentralized generation systems, modeling the detail of the power system and the grid, providing a secure and adequacy assessment of the grid, and studying long-term outlooks along with macroeconomic implications” [172].

Considering these modeling limitations and according to the time resolution and level of integration, the Nexus team proposes an integrated platform that consists of five modules, each is replaceable by different modeling tools. The first module is a CGE macroeconomic model that provides the analysis of the Swiss energy system at the national level. The second module determines capacity investments and generation expansion in the long-term view. The third module is an energy network model, that covers the detailed electricity network grid. The fourth modules analyses the decentralized energy generation and prosumers’ behavior. Finally, the fifth module is a security model that examines the energy system’s performance to shocks like loss of a specific power line or change in renewable energy generation (e.g. change in weather) [172]. The conceptual design of the model is presented in Figure A - 21 with five modules and their relations.

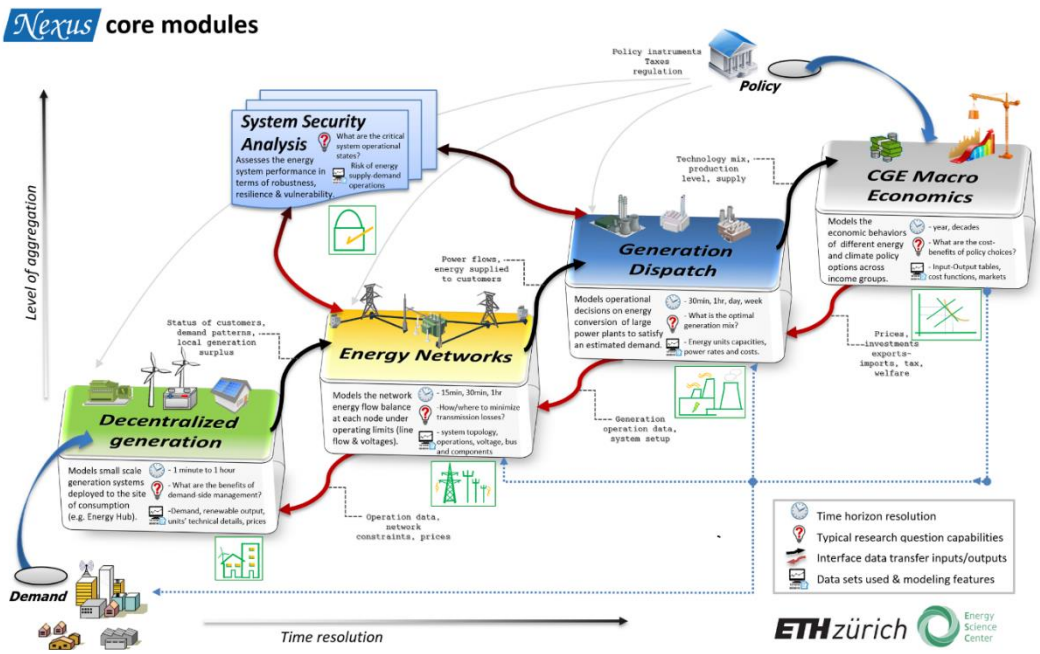

Figure A - 21, The overall representation of the Nexus integrated energy model.

Source: [172]

The Nexus framework suggests a conceptual design of an integrated energy system in order to analyze energy transition pathways to reach EU 2050 emission targets. Although it is an integrated energy framework, the Nexus team is only focused on the power sector and its implications on the macro energy system. The model is now being tested for analyzing nuclear phase-out scenarios for Switzerland. However, the Nexus team aims to broaden its perspective to answer questions like the behavior of decentralized flexibility options in highly deployed renewable energy supply systems. Or, the optimal mix of flexibility options in different policy designs. The pros and cons of this framework can be summarized as follows:

- Pros
  - Innovative conceptual design of an integrated energy system, which combines top-down and bottom-up approaches;
  - The modular design of the model, so each module can be substituted with different modeling tools;
  - Temporal and spatial resolution from the detailed local level to aggregate national (international) scope;
  - Considering new technological concepts and their effect on energy system like demand response, decentralized flexibility options.
- Cons
  - High data need;
  - No clear solution for linking the models;
  - Main focus on power system;
  - Not mature yet;
  - Assumptions behind each module of the framework are not clear.

2. EMP-E

The Energy Modelling Platform for Europe (EMP-E) is a forum for exchanging knowledge and research in energy system modeling across Europe. It was created in 2017 within the REEEM project and is now led by the four Horizon 2020 modeling projects funded under the call LCE21-2015 'Modelling and analyzing the energy system, its transformation and impacts': MEDEAS, REEEM, REflex and SET-Nav [177].

2.1. REEEM

The name of this project is an acronym for Role of technologies in an Energy-Efficient Economy – Model-based analysis of policy measures and transformation pathways to a sustainable energy system. This European project, which is part of the LCE21-2015 research program Horizon 2020, aims to provide an all-inclusive understanding of the implications of

energy transition strategies to a competitive low-carbon system in accordance with the Strategic Energy Technology Plan [178]. To support this aim, this project addresses four objectives:

1- Developing an integrated assessment framework;
2- Defining pathways towards a low-carbon society and assess their potential implications;
3- Bridging the science-policy gap through a clear communication using decision support tools;
4- Ensuring transparency in the process.

In order to reach these objectives, the project is divided into eight work packages. The University of Stuttgart leads the 6th work package on the energy system integration. Their objective is to develop an integrated European energy system model that is able to determine the impact of technological development, innovation, and EU policy measures.

The Stuttgart University team decided to follow an optimization approach by using the TIMES model [39] for EU28, Norway, and Switzerland. After importing the data into the model, it minimizes the discounted system cost considering all the constraints in the energy system. The TIMES PanEU is a modified version that covers the time period of 2010 to 2050 with 5-year time-steps. Each year is divided into twelve time-segments, four seasons with three time-steps of day, night, and peak.

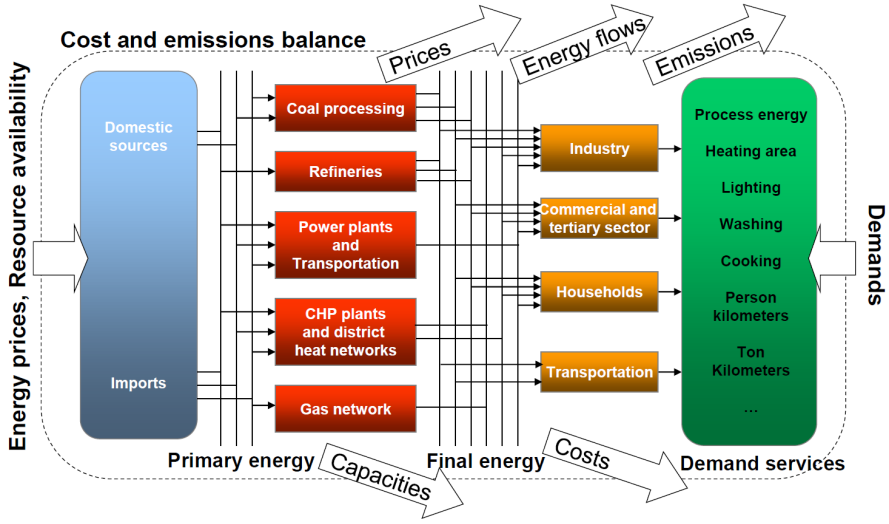

Figure A - 22, The TIMES PanEU model's schematic.

Source: [160]

2.2. SET-Nav

The project Strategic Energy Technology Navigation (SET-Nav) is a project under the Horizon 2020 program and aims to support strategic decision making in Europe's energy sector for a clean, secure, and efficient energy system. This project follows three main objectives, which are enhancing modeling capacities, strategic policy analysis, and stakeholder dialogue and dissemination across the EU [179]. The project is coordinated by the Technische Universität Wien (TU Wien) and is implemented by a multinational consortium of European research and industrial organizations.

The whole family of projects of MEDEAS, REEEM, REflex, and SET-Nav aims to develop a generic energy system model for Europe. The organization and motivation for this aim are particular. These projects, however, are pretty young and still without significant outcomes.

- Pros
  - European scope of the project invites many researchers and stakeholders to participate
  - The project has just started and so the results and development disseminations are up to date
- Cons
  - The very young age of the project and the lack of documented outcomes
  - The relation between the four projects is not clearly described

3. EUCALC

A consortium of several European institutes and universities started this joint project in 2016 [180]. This open source model aims to engage European and national policy makers, politicians, innovators, and investors. The novelty of this model is the interlink between the social, economic, and technical aspects of the energy system (Figure A - 23).

This simulation model is comprised of different core modules such as Lifestyle, Technology, Buildings, Transport, Industry, Agriculture, Power, and Biomaterials. Being a calculator in nature, the model provides several “levers” that the user can make a change in either the supply or demand of energy in a particular sector. The model assesses the energy demand based on lifestyle and activities performed in different sectors (e.g. room heating temperature). This assessment is linked with macroeconomic parameters in order to compute the demand elasticity to price. Afterward, the model calculates the economic impacts of demand drivers on jobs and the added value. The combination of all lever choices creates a scenario, and the model provides pathways based on the scenarios as an output.

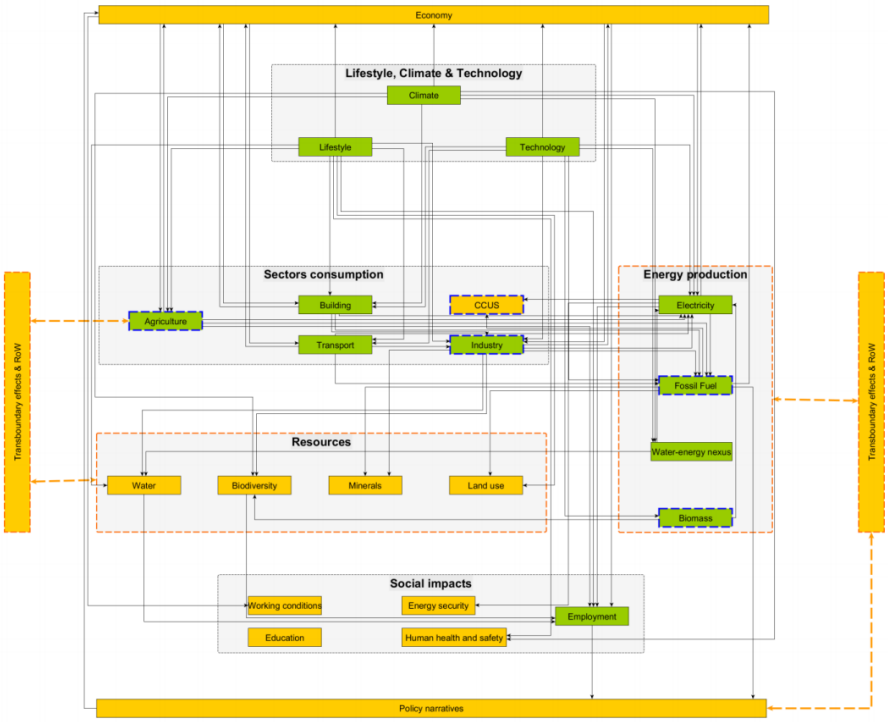

Figure A - 23, The schematic diagram of the EUCALC energy model, an interactive tool made for European and national policymakers.

Source: [181]

The model is written in Python and KNIME, which is an open-source data analytics, reporting and integration platform [182]. This interactive platform helps users to access the workflow detail quickly by zooming in each box (node).

Appendix B. Energy system modeling assessment

The reviewed models in Appendix A are assessed based on criteria mentioned in Table 4, i.e. technological detail and learning, temporal resolution, spatial resolution, social behavior, modeling methodology, database, accessibility, and application.

1. Technological detail and learning

When it comes to bottom-up modeling, the extent of technological detail plays a significant role. The quality of such a model is directly related to its rich set of current and future technologies. The technological detail's database is composed of three main subsets: (i) technological cost data (or techno-economic boundaries), (ii) technical limitations (or physical boundaries), and (iii) technological learning (or R&D boundaries). This database can be region-dependent as technological data may differ across different regions. Based on challenges of low carbon energy system modeling, four key parameters in the technological database of models are identified which are the inclusion of diurnal storage, seasonal storage, sectoral coupling options, and technological learning.

Model	Diurnal Storage	Seasonal storage	Sectoral coupling	Technological learning
DynEMo	Batteries	TES, PHES, HES	P2M, P2H, P2G	-
E4Cast	-	-	-	-
EnergyPLAN	Batteries	TES, PHES, CAES, HES	P2M, P2H, P2G	-
ENSYSI	Batteries	-	P2M, P2H, P2G	Exogenous, 1-factor ETL
ESME	Batteries	TES, PHES	P2H, P2G	-
ETM	Batteries	-	P2M, P2H, P2G	-
IKARUS	-	-	-	-
IWES	-	TES, PHES, HES	P2M, P2H, P2G	-
LEAP	-	-	-	-
MARKAL family	Batteries	TES, PHES, CAES, HES	P2M, P2H, P2G	Exogenous, 1-factor, ETL, MCL, MRL
METIS	Batteries	TES, PHES, HES	P2M, P2H, P2G	-
NEMS	-	PHES, HES	P2M, P2H, P2G	Exogenous
OPERA	Batteries	CAES	P2M, P2H, P2G	Exogenous
OSeMOSYS	Batteries	PHES	P2M, P2H	Exogenous
POLES	-	TES, PHES, HES	P2M, P2H, P2G	1-factor ETL
PRIMES	-	TES, PHES, CAES, HES	P2M, P2H, P2G	Exogenous, 1-factor ETL
REMix	Batteries	TES, PHES, CAES, HES	P2M, P2H, P2G	Exogenous
SimREN	-	TES, PHES, HES	P2H, P2G	-
STREAM	-	TES, PHES	P2M, P2H, P2G	-

Table B - 1, The technological detail and the technological learning of reviewed models

A brief description of the technological database of each model is listed in Table B - 1. The technological database can have either an international or national source. Models such as LEAP, MARKAL, TIMES, METIS, PRIMES, OSeMOSYS, POLES, and STREAM use international technical data from well-known sources such as IEA, IRENA, IPCC, and JRC-Europe. On the other hand, some models use national calibrated databases such as E4CAST (Australia), ESME (England), EnergyPLAN (Denmark, +374 technologies), ENSYSI (Netherlands, +250 technologies), OPERA (Netherlands, +300 technologies), IKARUS (Germany, +2000 technologies), SimREN (Japan), and NEMS (United States).

Almost all the reviewed models include sectoral coupling technologies as they are integrated ESMs. However, not all models include complete coupling between all sectors. ESME and SimREN models include P2H and P2G couplings while neglecting the link with the transport sector. This incapability can result in biased results on the role of EVs in the energy system.

Only a few models include a complete set of seasonal storage options. TES options can play a key role in further electrification of the energy system considering VRE sources. Most of the models with seasonal storage capability include PHES and CAES as these are established technologies; however, TES and HES are included only in some models such as EnergyPLAN, MARKAL family, PRIMES, and REMix. Intraday flexibility demand can be modeled by diurnal storage options which are included in only half of the reviewed models.

Although technological learning can have major effects on the energy modeling results, only half of the reviewed model include it. ETL is usually used in global scale models as the global cumulative production of technology determines its cost reduction. National energy models usually use exogenous learning rates based on global scenarios, while some models such as ENSYSI, PRIMES, and MARKAL family have the option of using 1-factor endogenous technological learning rate.

The key identified gaps are the following:

1- Lack of sectoral coupling technologies between electricity, heat, and transport sectors.
2- Lack of new seasonal storage technology options such as TES and HES.
3- Lack of endogenous technological learning rates.

7.1. Temporal resolution

The time parameter can be implemented in models in either continuous form or discrete time-steps. The continuous time manner implies the use of differential equations, which is computationally heavy. The discrete time-step, on the other hand, reduces the calculation load at the expense of losing temporal detail. Hence, the choice of time granularity should be based on the dynamics and application of the model. The long-run scenario analysis energy models are usually limited to yearly (or even 5-year) time-steps due to computational load, while electricity market models prefer hourly resolution in order to capture market dynamics and balancing (flexibility) issues.

Model	Temporal resolution	Time horizon
DynEMo	Flexible (e.g. hourly, monthly, yearly)	Up to 2050
E4Cast	Yearly	Up to 2050
EnergyPLAN	Hourly	Single Year
ENSYSI	Hourly	Flexible
ESME	Ten hourly time-slices	Up to 2050
ETM	Hourly	Up to 2050
IKARUS	5-years	Up to 2050
IWES	Hourly	Up to 2050
LEAP	Yearly (hourly time-slice for electricity)	Flexible
MARKAL, MARKAL-MACRO	Six hourly time-slices (only for electricity)	Flexible
TIMES	Flexible hourly time-slices	Flexible
METIS	Hourly	Single Year
NEMS	Yearly	25 years into future
OPERA	Flexible time-slices	Single Year
OSeMOSYS	Six time-slices	Flexible
POLES	Yearly	Up to 2050
PRIMES	Hourly time-slices	Up to 2050
REMix	Flexible hourly time-slices with chronological order	Flexible
SimREN	15-minutes	Up to 2050
STREAM	Hourly	Single Year

Table B - 2, The temporal resolution and the time horizon of reviewed models

The reviewed models differ greatly in their temporal resolution, from 15-minutes to 5-years' time-steps. IKARUS and OSeMOSYS models use the broad 5-years' time-step, making them suitable for scenario analysis at the expense of aggregating energy market and VRE sources. Optimization models with high technical resolution such as MARKAL, TIMES, OPERA, PRIMES, REMix, and ESME follow the time-slice approach in order to capture more detail of the energy system while satisfying computational constraints. ENSYSI analyses the electricity market on an hourly basis, and the rest of the energy system on a yearly resolution. Further temporal resolution is provided by EnergyPLAN, ETM, IWES, METIS, and STREAM models by using hourly time-steps in order to capture intermittent effects of renewable energies on the energy system.

The key identified gap is the following:

1- Lack of hourly temporal resolution for capturing intermittent renewables and their corresponding issues and potentials.

7.2. Spatial resolution

Conventionally, the aggregated national energy models neglect the location parameter in the calculations. Though, the decentralized energy system demands a segregated energy model that includes the location of the consumers and suppliers. The current ESMs at the national level have a diverse view on the spatial resolution of the model that is summarized in Table B - 3.

Model	**Spatial resolution**
DynEMo	National (No spatial depth)
E4Cast	National It is composed of seven regions for Australia, with separate energy markets for each region.
EnergyPLAN	National (No spatial depth) It can be applied at the regional/district level but still with no spatial depth.
ENSYSI	National (No spatial depth)
ESME	National, Regional It represents twelve onshore and twelve offshore (twenty-four in total) regions of the UK each with different energy demands, natural resources, technology choices, and infrastructure. Moreover, transmission and energy flow between regions is considered and demonstrated.
ETM	National (No spatial depth)
IKARUS	National (No spatial depth)
IWES	National, Regional The model consists of fourteen regions of Great Britain. The regions are connected through electricity and hydrogen transmission network. In each region the networks are divided into low demand density (rural) and high demand density (urban) networks.
LEAP	Multinational, National, Regional The user can specify the number of regions, each with a different database. Likewise, regional scenarios can be added to the model.
MARKAL family	Multinational, National, Regional The model comprises a number of user defined regions, each with a specific dataset. Interregional trade and conversion parameters can be defined by the user.
METIS	Multinational, National, Regional In METIS, geographical regions are represented by energy zones that can cover regions, a country, or a group of countries. Each energy zone has a delivery point in which energy demand/supply and transmission flows are balanced (i.e. Kirchhoff's first law). These delivery points have a geographical location on the map (i.e. longitude and latitude).
NEMS	National, Regional This model divides the United States into several regions. As it is mentioned in the model's description: "The demand modules (e.g., residential, commercial, industrial and transportation) use the nine Census divisions, the Electricity Market Module uses fifteen supply regions based on the North American Electric Reliability Council (NERC) regions, the Oil and Gas Supply Modules use twelve supply regions, including three offshore and three Alaskan regions, and the Petroleum Market Module uses five regions based on the Petroleum Administration for Defense Districts." [22]
OPERA	National (No spatial depth)
OSeMOSYS	National, Regional The user can define any number of regions, each with a specific database.
POLES	Multinational, National The model assumes sixty-six balancing regions (i.e. country or set of countries) across the globe. Therefore, it calculates regional energy prices based on regional demand/supply. Different energy carriers can be modeled in a different set of regions. For example, oil has a global market (all regions) and the gas market is modeled in fourteen regions.
PRIMES	Multinational, National Several regions (i.e. country or set of countries) are defined by default in the model, but the user can alter these regions or propose a new set of regions. The model balances the energy at each region with a separate market and different marginal costs.
REMix	Multinational, National, Regional Flexible multi-regions can be defined in the model. The model clusters GIS data of renewable energy sources as the input data for the installed capacity potential across regions.

SimREN	National, Regional The model divides Japan into twelve geographical regions that can exchange energy with each other. In each region, an energy manager controls the energy flow. In the national level, an import/export manager coordinates the supply of regions.
STREAM	National, Regional The user can define several regions each with a different database. The model balances each region based on demand/supply profiles.

Table B - 3, The spatial resolution of reviewed models.

The spatial scope of an energy system can vary from a neighborhood to a region, a country, or a set of countries. The resolution of a model is determined based on the energy system's size and the available data. However, the modeler is not completely free in this choice, as the available data and the computational power are limited. As a result, many simplifications should be made (e.g. assuming a single demand profile for all households in a country). Nonetheless, these simplifications can have a significant effect on the accuracy of the model results. Consequently, modelers are advised to increase the spatial resolution as long as the limitations allow it.

This study focuses on the national energy system, therefore, reviewed models have a national (in some cases multinational) spatial resolution. Models such as DynEMo, Energy PLAN, ENSYSI, ETM, IKARUS, and OPERA have one national spatial resolution. Usually, these models assume the energy demand and supply are connected throughout the system with simplistic costs or limitations assumptions, which can be called the copper-plate[1] assumption. On the other hand, regional models assume several regions inside a national boundary that results in an extra spatial layer of the model. E4Cast, ESME, IWES, NEMS, and SimREN have a fixed set of defined regions as these models are made each for a specific country with a particular geography. Instead, the user can add, remove, or alter the regions in LEAP, MARKAL family, METIS, OSeMOSYS, POLES, PRIMES, REMix, and STREAM. Among the reviewed models, the METIS model includes the geographical coordinates (i.e. longitude and latitude) as a parameter of the regions. Albeit, the added GIS parameter is limited to regions (as energy zones) and not inside regions. The inclusion of the detailed GIS data across the energy system requires a huge computational capacity and an enormous database. The METIS model's approach to allocating GIS data to regions can be considered a step forward.

The key identified gaps are the following:

1- Lack of regional spatial resolution for analyzing energy flows between regions across a country.
2- Lack of fine geographical resolution options, such as GIS, fine mesh, and clustering, for analyzing decentralized intermittent supply and infrastructure costs and benefits.

7.3. Social parameters

Some actors in the energy system (i.e. prosumers, municipalities, and governments) can have an adaptive nature rather than a rational behavior. They learn from their activities by making imperfect decisions, while communicating with others. Their decisions can be dependent not only on economical parameters but also on socio-economic parameters such as stakeholders' energy demand profiles, learning, risk profiles, communication with others, perceived environmental values, and perceived discount factors. The behavior of stakeholders results from a complex mixture of these parameters considering their bounded rationality[2]. Therefore, stakeholders tend to take "satisfactory" decisions rather than "optimal" decisions. Modeling satisfactory decisions is a challenge due to the complexity of decision making procedures, high dependency of parameters on empirical studies, lack of empirical datasets, and a need for additional processing power.

The energy system is a complex adaptive system, which basically means understanding each component of it will not lead to an understanding of the whole system [183]. Axelrod [184] argues that "the simulation of agent-based models is often the only viable way to study populations of agents who are adaptive rather than fully rational". ABMs are aiming to demonstrate possible system outcomes (which may not be necessarily optimal) while illustrating the corresponding emergent transition paths.

Model	Inclusion of socio-economic parameters
DynEMo	Consumer load profiles
E4Cast	Consumer load profiles

[1] A power system that allows a perfect (i.e. lossless, unrestricted, and unlimited) electricity flow across suppliers and consumers.
[2] A notion that implies decision makers' decision is affected by their limited available information, limited cognitive capacity, and limited decision making time.

EnergyPLAN	Consumer load profiles
ENSYSI	Eight Agent groups, Four Agent types based on Roger's diffusion of innovation theory
ESME	Consumer load profiles
ETM	Consumer load profiles
IKARUS	Consumer load profiles
IWES	Consumer load profiles
LEAP	Consumer load profiles
MARKAL family	Consumer load profiles
METIS	Consumer load profiles
NEMS	Consumer load profiles
OPERA	Consumer load profiles
OSeMOSYS	Consumer load profiles
POLES	Consumer load profiles
PRIMES	Agent groups, non-perfect regimes, heterogeneous agents
REMix	Consumer load profiles
SimREN	Consumer load profiles
STREAM	Consumer load profiles

Table B - 4, The presence of behavioral parameters in reviewed models

From the reviewed models, only two models address stakeholder's behavior by the agents' interactions; while, others only include consumer load profiles as the behavioral input to the model. ENSYSI includes eight groups of actors (i.e. agents) in the energy system which are National, Consumer, Housing Association, Farmer, Government, Company Small, Company Medium, and Company Large. Each group has different tax and discount rate preferences. Further, each group consists of four different actor types, which are Innovators, Early Adopters, Majority, and Laggards based on Roger's diffusion of innovation theory [86]. Each actor type has different decision preferences that can be adjusted by the user. PRIMES emphasizes on techno-economic decision parameters of agents rather than socio-economic parameters. Agents can be price-takers as demanders and price-makers as suppliers. Demand agents maximize their benefit subject to several techno-economic constraints. Supplier agents minimize the costs to meet demand subject to a different set of techno-economic constraints. The model can simulate the imperfect market conditions and optionally include Nash-Cournot[1] competition.

The key identified gaps are the following:

1- High dependence of ESMs on consumer load profiles.
2- Simplistic modeling of social behavior in current ABMs.

7.4. Modeling methodology

The methodology describes a set of procedures or practices to be followed in order to reach an objective. Energy models can be classified based on their methodology: Optimization, Simulation, Multi-Agent, Partial Equilibrium, Spreadsheet, Computable General Equilibrium (CGE), Input-Output, Integrated Assessment, Multi-Criteria, System Dynamics, Macroeconomic, Microeconomic, Stochastic, Spatial (GIS), Accounting, Backcasting, and Econometrics.

It is difficult to observe a consistent classification of modeling methodologies. Nakata [185] considers optimization, simulation, and equilibrium as the three main energy economics modeling methodologies. Similarly, a recent review of energy modeling tools with high shares of renewables acknowledges the three main methodologies [9]. Horschig and Thran [7] divide top-down models into equilibrium and input-output models while dividing bottom-up energy models into simulation and optimization models. Despres et al. [186] classify long-term energy models based on simulation and optimization methodology.

An integrated ESM may follow an optimization approach, in which the primary aim is to provide the scenario of the (unique) optimized system evolution, or a simulation approach, in which the primary aim is to provide a set of scenarios of how the system may evolve [6]. Optimization and simulation methodologies may sometimes overlap or even be used in a hybrid way. The main difference between the two methodologies is that the optimization model optimizes the

[1] The Cournot model assumes that rival firms produce a homogenous product in a specific quantity, based on rivals' quantity. It will lead to a (non-Pareto) Nash equilibrium, which is called Nash-Cournot equilibrium.

outcome of a certain scenario based on certain assumptions – in terms of minimizing costs or maximizing (social) returns (welfare) – within certain technical, socioeconomic, or policy constraints; while the simulation model does not necessarily optimize the modeling outcomes but rather analyses certain scenarios (based on certain assumptions and input values). A figurative distinction between these two methodologies is illustrated in **Error! Reference source not found.**.

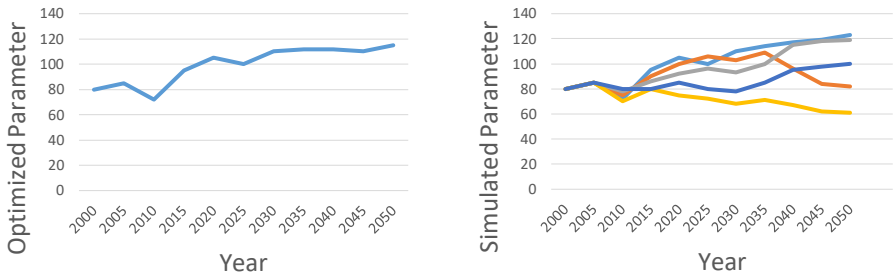

Figure B - 1, A symbolic distinction between optimization and simulation methodologies.

The optimization methodology aims to find the assumed unique optimal solution, while the simulation methodology maps feasible solutions

Source: [187]

Hourcade et al. [188] divide bottom-up models into descriptive and prescriptive models. The first provides a practical estimate of the technology mix based on complex preferences such as intangible costs, uncertainty, market barriers, and capital constraints. While the other delivers an estimate of the technological potential by minimizing explicit costs for a given system. Although both simulation and optimization methodologies may follow a descriptive or prescriptive approach [188], generally optimization models are of a prescriptive and simulation models of a descriptive nature [187].

Mathematical approach

Optimization models may be classified based on their mathematical approach, which determines the underlying programming approach of the model. The common approaches[1] are Linear programming, Mixed-integer programming [189], Dynamic programming [190], and, recently, Agent-based programming [191]. The first three approaches are mainly used in optimization models, while the last one (i.e. agent-based programming) may be used in simulation models. It may happen that a single model incorporates several approaches in order to get proper results.

Linear Programming (LP) either maximizes or minimizes a linear objective function based on a set of constraints (e.g. balanced supply and demand). This approach is static in nature and does not consider the evolution of parameters.

Mixed-integer Programming (MIP) is an extension of Linear Programming that particularly forces some variables to be integral in order to capture the discrete nature of some decision variables. This method is used when an energy model includes an integer parameter such as the state of a power plant or the number of wind turbines.

Dynamic Programming (DP) is used to find the optimal pathway. It ensures the optimality not only in a single time step, but also across the time horizon. The core idea of DP is to break up the problem into several overlapping sub-problems and incorporate the results of other sub-problems for optimizing the state of the system.

Multi-Agent Programming (MAP) is a computational framework for simulating the interactions of autonomous agents with the aim to evaluate the overall system behavior. It is used in Agent-Based Models (ABMs) to capture the market's imperfections such as strategic behavior, bounded rationality, and asymmetric information. Due to its particular advantages, Chappin [191] considers it to have the largest potential for the studies in the energy systems transition compared to other simulation modeling paradigms (i.e. CGE, System Dynamics, and Discrete Event Simulation).

Model (developer)	**Modeling methodology**	**Calculator**
DynEMo (UCL)	Simulation (Spreadsheet)	+
E4Cast (ABARE)	Partial Equilibrium	-
EnergyPLAN (Aalborg University)	Input-output	+
ENSYSI (PBL)	Multi-agent simulation	-
ESME (ETI)	LP Optimization	-

[1] In addition, newer approaches are being developed such as multi-criteria techniques [217], [218] or fuzzy logic [219].

ETM (Quintel Intelligence)	Simulation	+
IKARUS (Research Center Jülich)	LP Optimization, Simulation, Input-output	-
IWES (Imperial College London)	Optimization	-
LEAP (Stockholm Environmental Institute, USA)	Accounting	+
MARKAL, MARKAL-MACRO, TIMES (IEA)	LP, MILP, DP Optimization	-
METIS (DG ENER)	Simulation, Optimization	-
NEMS (EIA)	Simulation, Optimization	-
OPERA (ECN)	LP Optimization	-
OSeMOSYS (KTH, UCL, others)	LP Optimization	-
POLES (European Commission)	Simulation, Partial Equilibrium	-
PRIMES (NTUA)	Multi-agent simulation, LP Optimization	-
REMix (DLR)	MILP Optimization	-
SimREN (ISUSI)	Simulation, Optimization	-
STREAM (Ea Energy Analyses)	Simulation, Spreadsheet	+

Table B - 5, An overview of the modeling methodology of reviewed models

Some energy models mainly aim to engage policymakers, businesses, NGOs, and other actors of the energy system in society. These energy models calculate the energy system by simulating the energy system based on user's input values, therefore sometimes they can be called energy calculators. These models do not propose an optimum output, instead, they provide a framework to monitor different possible futures based on the specified user-defined scenarios. Calculator models in Table B - 5 use spreadsheet, input-output, or accounting methodologies.

7.5. Data use

When it comes to modeling real-world phenomena, the first limitation is the availability of the data. It is one of the main concerns in energy system modeling as energy data is often sensitive, strategic, non-accessible, difficult to measure, or costly. Consequently, data gathering is a challenging part of energy modeling, and actually it determines to what extent a model can be used. For each of the reviewed models, a summary of input data used is described in the following Table B - 6.

Model	**Data Source**
DynEMo	No specific description of the input data. The model utilizes Excel tabs to manage data about different technologies, environment, and fuels.
E4Cast	Demand parameters are derived econometrically using historical Australian energy data from BREE's Australian Energy Statistics. 40 electricity generation technology data from BREE. Future fuel prices data from BREE.
EnergyPLAN	The model uses three main data inputs: Costs are imported from a database, which contains +374 different technology costs that mostly are derived from DEA [192], thus calibrated to Denmark. The user should import technology costs manually if the case study is unlike Denmark energy system. Distribution profiles (electricity demand profile, wind power production profile, and district heating demand profile) on an hourly basis are imported in text files with 8784 lines (corresponding to hours in a year). The model comes with Danish distribution profiles by default. Energy system assumptions. The model has been used to study different countries. Datasets for different countries are available online [193].
ENSYSI	The model comprises three main data inputs: Economic indicators such as the number of houses and offices, transport kilometers, and economic development of industry. Prices of primary energy carriers such as coal, oil, natural gas, and biomass. Cost parameters of +250 technologies including technological learning over the simulated time period. The base year data is imported from MONIT. The technology database is based on another Dutch ESM, eDesign, which is developed by PBL. Moreover, the database uses many different public sources (e.g. the data on different actors and their decision-making preferences).
ESME	This model has three main data inputs: Annual demand estimates from 2010 to 2050 in each UK region are imported to the model from the UK government database (Open Source). Cost and performance parameters of +250 energy technologies (proprietary data derived from ETI projects).

	Set of assumptions on energy source parameters, like global energy costs, the carbon content of energies, etc.
ETM	This model uses three main data inputs: Energy balances of the country are obtained from the IEA energy reports (proprietary licensed to iea.org). Assumptions of the energy system such as population and a fraction of LED lamps (open-source). Technological assumptions such as efficiency, operation, and maintenance costs (open-source).
IKARUS	The model uses a consistent dataset, including capacities, efficiencies, costs, emissions, and technical restrictions. It describes ~2000 technologies, the demand for energy services, and the import of primary energy sources. Apparently, this database is in the possession of the German federal government.
IWES	The model uses the UK Department of Energy and Climate Change data. In some cases when the data is not available the model uses an assumption, for example, the regional data for hydrogen storage is aggregated from a statistical regression method.
LEAP	This model uses a Technology and Environmental Database (TED) that describes the technical characteristics, costs and environmental impacts of hundreds of energy technologies including existing technologies, current best practices, and next-generation devices. TED's data is mainly supplied by the IPCC, U.S. Department of Energy, and IEA reports. TED also includes qualitative information pages that review the availability, appropriateness, cost-effectiveness and key environmental issues for a wide range of energy technologies. The database is editable by the user.
MARKAL family	One of the main distinguishing factors of this energy model is the emphasis on the technological database. It comprises an open source qualitative and quantitative database with extensive detail on technology, demand, and supply that is developed by ETSAP and IRENA [194]. The qualitative data includes, for example, lists of energy carriers, the technologies that the modeler feels are applicable (to each region) over a specified time horizon, as well as the environmental emissions that are to be tracked. Quantitative data, in contrast, contains the technological and economic parameter assumptions specific to each technology, region, and time period [39].
METIS	It requires as inputs the following types of data (up to hourly granularity): Capacity and technical characteristics of infrastructure, Capital and technology costs, Fuel prices, CO2 emission factors and prices, Weather data (actual data and forecasts), Wind, solar and hydro profiles, Demand profiles and Level of demand. The main sources of data are DG ENER's EMOS database [195], ENTSO-E [196] and ENTSO-G [197] databases as well as Eurostat. Weather data are provided by ECMWF [198]. Although, A significant part of the input is context dependent.
NEMS	Although the model is open-sourced under iea.org public license, it contains some proprietary components such as Intel Visual Fortran, GAMS, AIMMS, and the Xpress optimizer (Fair-Isaac). The model employs the Global Data Structure that defines all NEMS intermodule variables. It is mainly supplied by EIA datasheets, though it uses some other non-EIA datasheets. The model together with input data is accessible online [164].
OPERA	The model consists of detailed ~500 technologies in production, conversion, transport, storage, and demand (proprietary). Demand and supply profiles are fed into the model on an hourly basis. It uses the annual National Energy Outlook (NEO) of the Netherlands as a baseline to get information on total emissions, energy service demand per sector, conversion characteristics of technologies used in NEO, volumes and capacities of technologies, and prices of primary energy carriers (open-source). The technology portfolio is based on the complete energy balances of the Netherlands that are reported in MONIT. These energy balances distinguish between energetic energy use, non-energetic use (feedstock in e.g. the petrochemical industry) and other energy conversions (e.g. cokes ovens or refineries) [24].
OSeMOSYS	The data requirements include energy demand for the activities that are considered in the model and an annual (hourly) load curve for the relevant demands; Technology-specific efficiencies, Electricity generation capacity, technology specific factors (capacity/availability), construction time, lifetime; Technology costs (capital, fixed and variable O&M), Fuel costs (both local and imported costs); Resource potential (fossil fuel reserves, renewable energy potential), water availability for hydropower plants; Emissions accounting and corresponding fuel specific emission factors. The model uses the open source database of ETSAP, IEA, and World Bank [199].
POLES	The database in this model consists of socio-economic (population, GDP, growth, etc.), energy balances, GHG emissions, and technology costs parameters. The data for each sector come from various sources such as Eurostat, World Bank, Enerdata, BP, etc. The model runs in a recursive way, so the output projection data is fed into the model as input for the next time-step (endogenous). The extensive list of the input data and the related sources are accessible on [28] page 54.
PRIMES	Major inputs to the database of this model such as energy balances, energy prices, population, co2 emission factors, macroeconomic data, etc. come from Eurostat (open-source). Technology database of the model is fed by the output of several studies such as MURE, ICARUS, ODYSSEE, NEMS model database, VGB (power technology costs), IPPC BAT technologies, etc (open-source). Several other data inputs for power plant inventory, RES potential, and network infrastructure come from other studies and other databases such as ECN, DLR, EurObserv'ER, PLATTS, ESAP SA, ENTSOE, and GIE (Partly open-source).

	The complete list of model's data sources is accessible on [30] page 25.
REMix	The input data is processed using the REMix-EnDAT model. REMix-EnDAT contains global datasets for renewables with high spatial and temporal resolution. The model processes the raw global data (i.e. GLC2000 [200]) in order to determine the installation capacity of each renewable technology in each pixel (300*300 m^2 grid).
SimREN	The model uses an input database (e.g. renewable energies, demand curves, and weather data), that is supplied by the Institute for Sustainable Energy Policies (ISEP). Japanese energy demand data from the year 1999 was chosen as a reference year for the demand model and weather forecasts. Typical annual and daily load curves and the total annual consumption of the sectors in the regions serve as the basis for the calculation [35]. A weekday and a weekend demand curves for each season are used as the hourly resolution of daily load curves.
STREAM	All the datasets used by STREAM are imported from other publicly available sources (e.g. Eurostat).

Table B - 6, The input data of reviewed models.

The quality of a dataset is determined by several characteristics such as accuracy and precision, legitimacy and validity, reliability and consistency, timeliness and relevance, completeness and comprehensiveness, availability and accessibility, and granularity and uniqueness. Many of the models use open-source databases from an international organization such as IEA or Eurostat. Some others use national open-source databases such as DEA or EIA. REMix uses a global high temporal and spatial resolution database for estimating the capacity potential and hourly profile of renewable sources in each region as well as power and heat demand (i.e. GLC2000 [200]).

The key identified gaps are the following:

1- Focus of current datasets only on technological detail, rather than stakeholders' behavior.
2- Lack of spatially resolved datasets such as infrastructure and local storage.

7.6. Accessibility and Application

Open access to the model provides an opportunity for other researchers to replicate the study and even provide further insights. Moreover, it increases the number of users, which leads to a higher quality of the model and a higher rate of model applications. Further, it promotes the transparency of the studies. Table B - 7 demonstrates the accessibility and application of reviewed models.

Model	Accessibility	Application
DynEMo	Limited Access	UK and France [201]
E4Cast	-	Australia [21]
EnergyPLAN	Free to Download	Applied extensively to many countries especially Denmark [202]
ENSYSI	Free upon request (not online)	No application.
ESME	-	Applied to the UK for low carbon technology assessment [27]
ETM	Free online	Netherlands [203], [204]
IKARUS	-	Germany [155]
IWES	-	UK [34]
LEAP	Commercial, free for developing countries and students	More than 32 countries used LEAP to report energy and emissions scenarios to UNFCCC [205]
MARKAL family	Commercial	Applied extensively to many countries and regions [4]
METIS	-	Different studies at European level [206], [207], [208], [209]
NEMS	Free, simulators must be purchased	Mainly used in U.S. EIA Annual reports
OPERA	Free upon request, the solver must be purchased	The Netherlands [24]
OSeMOSYS	Free online	Applied to Cyprus, European REEEM project [210], South America [211], Electricity in Africa
POLES	Limited access	UK [212], France [213], European Commission [214]
PRIMES	Commercial	European Commission [215]
REMix	-	EU [216], Germany [33], Brazil [217], Morocco [218], Botswana [219]
SimREN	-	Japan [35]
STREAM	Free online	Denmark [170], [220]

Table B - 7, The accessibility and the application of reviewed models

Open-source models such as the MARKAL family, EnergyPLAN, and OSeMOSYS have been used in many case studies, while private models such as IKARUS, E4Cast, and ESME have been used in one country.

The key identified gaps are the following:

1- Limited accessibility of current models
2- Lack of documentation on models' assumptions and methodologies