Energy systems modeling for twenty-first century energy challenges

Stefan Pfenninger[1,*] Adam Hawkes[2] James Keirstead[1]

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[*] Corresponding author: stefan.pfenninger@imperial.ac.uk.

[1] Department of Civil and Environmental Engineering, Imperial College London

[2] Centre for Environmental Policy, Imperial College London

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Abstract

Energy systems models are important methods used to generate a range of insight and analysis on the supply and demand of energy. Developed over the second half of the twentieth century, they are now seeing increased relevance in the face of stringent climate policy, energy security and economic development concerns, and increasing challenges due to the changing nature of the twenty-first century energy system. In this paper, we look particularly at models relevant to national and international energy policy, grouping them into four categories: energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios. We examine four challenges they face and the efforts being taken to address them: (1) resolving time and space, (2) balancing uncertainty and transparency, (3) addressing the growing complexity of the energy system, and (4) integrating human behavior and social risks and opportunities. In discussing these challenges, we present possible avenues for future research and make recommendations to ensure the continued relevance for energy systems models as important sources of information for policy-making.

Keywords: energy systems modeling; energy policy

1 Introduction

Hamming (1962) argued that the purpose of computing is insight, not numbers. The development of energy systems models is clearly linked to this need for insight, and the discussion on using them not just for numbers is as old as the models themselves (e.g., Huntington et al., 1982). Energy policy as a distinct field began in earnest in the wake of the oil crisis in the seventies, when both industry and policymakers realized the importance of long-term strategic energy planning (Helm, 2002). In order to formally represent the complexity of interactions and multiple layers of energy across a modern economy, the methods of linear programming in use for large-scale planning since the second world war were used to develop the first energy systems models (Dantzig, 1965). The International Energy Agency (IEA) was founded in

1974, and its Energy Technology Systems Analysis Program (ETSAP), intended to develop an energy systems model, was launched in 1976. The International Institute for Applied Systems Analysis (IIASA), founded in 1972 as a center for scientific collaboration between east and west, also began efforts to develop an energy systems model soon after its founding. Both of these models remain important today. Although initially developed for use primarily in the EIA member countries and other large developed economies, these and later models have since been used for analysis in a wide range of contexts ranging from small off-grid systems in developing countries (e.g. Pina et al., 2011; Ghosh et al., 2002; Wright et al., 2010) to large-scale continent-wide analyses in developed economies (e.g. GEA, 2012; Gracceva and Zeniewski, 2013).

The development of energy systems models can also be linked to the rising importance of scenario planning throughout the twentieth century. According to Chermack et al. (2001), after being pioneered at the RAND Corporation in the 1940s as "future-now thinking", an increasing focus on scenario planning was again one of the lessons learned from the oil crisis in the seventies. Energy systems models helped analysts understand a sector that had grown increasingly complex, and to develop scenarios about its possible future evolution. But energy systems models did not just allow for the development of scenarios, they also made possible the formalization of scattered knowledge about the complex interactions in the energy sector, and a structured way of thinking about the implications of changes to parts of the system. Most importantly, they allowed policy-makers to explicitly state their views on the direction the energy sector should be steered towards in order to fulfill given policy goals.

Energy is closely linked to a confluence of key problems and opportunities, and in the twenty-first century this is driving a renewed effort to improve the model-based analysis of energy systems. The challenges include security, affordability and resilience of energy supply, as well as environmental concerns, ranging from local air and water pollution to, most importantly, climate change and global sustainability. But there are also opportunities: bringing new technologies to market, building competitive new industries, and providing vast new sustainable energy production to those parts of the world experiencing rapid economic growth.

While energy systems models were initially focused more on energy security and costs, climate change policy has since emerged as a powerful factor driving many studies, with a focus on pathways to achieve the significant reductions in greenhouse gas emissions called for by climate science (Meinshausen et al., 2009). Such mitigation scenarios are presented at a global scale for instance in the Global Energy Assessment (GEA, 2012), at a European scale in Schellekens et al. (2011), and at a United Kingdom scale in MacKay (2009) or Committee On Climate Change (2011). Because some end-use sectors (such as air transport) are difficult to decarbonize using available technology, a common theme in these studies is the need to achieve deep emissions reductions in the electricity sector, and an increase in electricity production to electrify ground transportation as well as heating and cooling. Renewable energy sources, particularly wind and solar power, play a critical role in these low-carbon electricity systems.

In this context, the established methods to model energy systems at a national and international scale are being challenged by several emerging issues: (1) the rise of flexible demand driven by new technologies such as smart meters and distributed generation, (2) the importance of electrification and intermittent supply, with the resulting need for more temporal detail, and (3) the new paradigm of distributed energy and varying renewable resource potential with the resulting need for more spatial detail. None of these issues were of concern for twentieth-century energy systems based primarily on large-scale centralized electricity production and fossil fuels.

For example, questions about the viability of renewable energy are widely debated. While one study may suggest high costs due to intermittency without adequate storage (Gross et al., 2006), others show that close to 100% percent of power supply can be met by renewables at feasible costs (Budischak et al., 2013). A traditional energy systems model is unable to assess such competing claims, yet now that a transition to a renewable energy system is under serious consideration, such questions become important. Scenarios produced by the large energy systems models can produce aggregate cost figures and decarbonization targets, and can thus reiterate and refine the argument for decarbonization, but they cannot answer questions about feasible configurations of a real renewables-based energy system or the possible roadblocks that stand in its way (UKERC, 2013). Thus, recent modeling efforts are attempting to deliver the necessary spatial and temporal resolution that can help answer these questions (Haller et al., 2012b; Pfluger and Wietschel, 2012; Fripp, 2012).

In this paper we examine how energy systems modeling is changing to address these challenges, and describe both how existing and well-established models are adapting and the types of new models that are emerging. To do so, we identify and discuss four key groups of energy systems models with an important role in underpinning national and international energy policy in Section 3. This highlights four important challenges which are discussed in Section 4, and we examine the efforts taken to address them. Finally, in Section 5, we examine the implications of our review for energy systems modeling and energy policy.

2 Method

We define an "energy system" as the process chain (or a subset of it) from the extraction of primary energy to the use of final energy to supply services and goods (i.e., the definition given in GEA, 2012). In other words, an energy system encompasses the "combined processes of acquiring and using energy in a given society or economy" (Jaccard, 2005). The building blocks of a model to depict such a system can thus include technical, environmental and even social elements, but most models focus on the former two. The energy modeling landscape is vast, but we are here interested in models that look at the systems aspect and the interaction between the energy system and the wider economy. We therefore exclude models and methods that deal with only one specific subset of problems, such as quantifying the potential for a specific technology.

For our review, we draw on several recent analyses of energy systems models with different emphases (see Table 1). There are two recent broad overviews of energy models, Jebaraj and Iniyan (2006), which contains a listing of models published up to 2005, ranging from demand-focused models through planning, policy, and operation models, and Bazmi and Zahedi (2011), who focus on power sector and optimization models in particular, looking at models ranging from plant operation, power distribution, consumption in residential and industrial buildings, through to larger-scale systems models for policy and planning. Both of these reviews are very broad and thus are not intended to give insight into detailed issues within the various model families they cover. More focused reviews recently published deal with electricity market modeling (Ventosa et al., 2005), small-scale and decentralized energy planning (Hiremath et al., 2007), the integration of renewable energy into existing systems (Connolly et al., 2010), agent-based models (Sensfuß et al., 2007), stochastic models (Möst and Keles, 2010), urban energy systems (Keirstead et al., 2012), and the availability and openness of code and data (DeCarolis et al., 2012).

We focus on four paradigms of models and discuss representative examples to illustrate their salient features: (1) energy

Table 1: Relevant recent reviews of energy system models and related work

Publication	Focus	Coverage
Jebaraj and Iniyan (2006)	Overview of energy models	252 publications
Bazmi and Zahedi (2011)	Overview of power sector optimization models	277 publications
Ventosa et al. (2005)	Electricity market modeling	36 models
Foley et al. (2010)	Electricity system models	7 models
Hiremath et al. (2007)	Decentralized energy planning	74 models
Sensfuß et al. (2007)	Agent-based electricity market models	14 groups of models
Möst and Keles (2010)	Stochastic electricity market models	20 models
Connolly et al. (2010)	Renewables integration	37 models
Keirstead et al. (2012)	Urban energy system models	219 publications
DeCarolis et al. (2012)	Openness of code and data	12 models

systems optimization models, (2) energy systems simulation models, (3) power systems and electricity market models, and (4) qualitative and mixed-methods scenarios. There are other ways to group models, but these four highlight key groups of energy systems models relevant to energy policy with important differences amongst each other. We delineate the four paradigms as follows:

1. models covering the entire energy system, primarily using optimization methods, with the primary aim of providing scenarios of how the system could evolve,
2. models covering the entire energy system, primarily using simulation techniques, with the primary purpose of providing forecasts of how the system may evolve,
3. models focused exclusively on the electricity system, ranging in methods and intentions from optimization/scenarios to simulation/prediction,
4. scenarios relying on more qualitative or mixed methods rather than detailed mathematical models.

From our distinction between groups (1) and (2), it is clear that one important axis along which we can differentiate models is the dichotomy between two method and purpose pairs: simulation/forecasts, and optimization/scenarios. In general, we can say that the intention of the first pair is predictive, while that of the second pair is normative. In practice these boundaries can be fluid, and models can be anywhere along a continuous scale between these two extremes depending on the context they are used in and data used as a basis for the analysis. A second dichotomy is related to, but distinct from, the first one: planning models versus operational models. While energy systems models are usually intended for planning purposes, the importance of high-resolution analysis of varying demand and renewable energy has led to an increased importance of operational models, and an increased necessity for the amalgamation of planning and operational perspectives into single models, as we will see. In the domain of power systems, we see this dichotomy in the difference between capacity expansion models (planning) and dispatch models (operational). Finally, and again related, is the dichotomy between snapshots and pathways: e.g., merely providing a snapshot or a desired end state for a system, or a pathway for reaching that end state.

Table 2 gives an overview of the four paradigms and what purpose they usually focus on. Our aim is not a formal classification of model types, but a discussion of the main types of energy systems models relevant for the analysis of modern energy systems at national and international scales. We also do not aim to discuss or compare modeling results between different countries. The issues we identify apply equally to the different country contexts in which energy system models have been applied. More formal attempts at classifying energy systems models by various criteria can be found for example in Jebaraj and Iniyan (2006) and Connolly et al. (2010). A list of all acronyms and models mentioned in this paper can be found in the Appendix table.

Table 2: The four model groups

Model family	Examples	Primary focus
Energy system optimization models	MARKAL, TIMES, MESSAGE, OSeMOSYS	Normative scenarios
Energy system simulation models	LEAP, NEMS, PRIMES	Forecasts, predictions
Power system and electricity market models	WASP, PLEXOS, ELMOD, EMCAS	Operational decisions, business planning
Qualitative and mixed-methods scenarios	DECC 2050 pathways, Stabilization wedges	Narrative scenarios

3 Current paradigms and challenges

This section examines the four model groups while introducing the four challenges. The order in which the models and challenges are discussed does not suggest that particular paradigms are particularly affected by the challenge following them, rather it serves to organize the discussion as clearly as possible.

3.1 Paradigm: Energy system optimization models

Large bottom-up optimization models have long been the backbone of energy systems modeling. Bottom-up models are based on a detailed description of the technical components of the energy system. Because of their rich detail they need to make simplifications to remain tractable, for instance, limiting themselves to nationally aggregated technology build and yearly or seasonally averaged supply-demand balancing. Two important established bottom-up model families are MARKAL/TIMES (Fishbone and Abilock, 1981) and MESSAGE (Schrattenholzer, 1981). MARKAL is possibly the most widely used general purpose energy systems model. With the addition of another optimization model, EFOM (Energy Flow Optimization Model), it evolved into TIMES (The Integrated MARKAL-EFOM System, Loulou and Labriet, 2008). This in turn has been developed into TIAM (TIMES Integrated Assessment Model), a global version of TIMES with additional functionality for climate response modeling. The entire MARKAL/TIMES family is developed by the IEA ETSAP, which is a consortium of researchers from IEA member countries, with the mission to maintain energy systems modeling capacity amongst its members. Its models are publicly available via the IEA ETSAP.

The MARKAL/TIMES and MESSAGE families have very similar purposes: to represent possible evolutions of the energy system on a national, regional or global basis over several decades, without necessarily being able to say anything about how likely these evolutions are. Both have originally been linear optimization models designed to minimize total energy system cost. More recent versions include non-linear and mixed integer linear formulations. For instance, the MARKAL Elastic Demand version meets energy service demands with own-price demand elasticities, and maximizes the sum of producer and consumer surplus (UKERC, 2013). Another important innovation was the development of hybrid models in the 1990s (Hourcade et al., 2006). These hybrids link technologically rich bottom-up models with top-down general equilibrium economic models that bring marginal abatement cost curves or production functions to attempt to characterize economy-wide movements in response to energy system changes. Again, the MESSAGE and MARKAL families provide important examples. MESSAGE-MACRO (Messner and Schrattenholzer, 2000) consists of two separate soft-linked models: the linear MESSAGE model with the nonlinear MACRO macroeconomic model. Soft-linking means that the two linked models are iteratively solved, with results from one model feeding into the next run of the other model, in an iterative approach that (ideally) leads to convergence. In contrast, MARKAL-MACRO (Manne and Wene, 1992) hard-links the two models into one fully integrated single iteration solution product.

Hybrid models can deliver insights that pure bottom-up models cannot (Strachan and Kannan, 2008). Despite the advance of this newer generation of hybrid models, computational limitations still mean that trade-offs have to be made between technical/engineering detail and economic detail. The availability of hybrid models has also not displaced the original pure bottom-up optimization models; both MARKAL and MESSAGE are still widely used in current research. Despite the dominance of these well-established model families, efforts to produce new models within the same tradition are still ongoing. An important example of a new MARKAL-style model currently under development is OSeMOSYS (Howells et al., 2011). Its innovation is a completely open source code base, the potential significance of which is discussed below.

3.2 Challenge: Resolving details in time and space

The discussion of large bottom-up optimization models leads to a first important challenge: balancing model resolution with data availability and computational tractability. Traditionally, the bottom-up energy systems models consider spatially aggregated regions and either a single time slice per year or a small set of seasonal and daily time slices, e.g. to represent differences between summer and winter demand. A coarse spatial and temporal resolution is necessary to keep models solvable within reasonable time and to reduce calibration and other input data requirements. But it is also a sensible simplification when dealing with situations where temporal fluctuations are not important. This is the case for an energy system based predominantly on fossil fuel-fired or nuclear plants, which can be assumed as either baseload or dispatchable at will, and whose output has a negligible dependence on fluctuating external influences such as the weather.

However, renewable energy can be highly variable in time, and energy demand may become much more actively managed in future energy systems. Therefore, with their rising importance, resolving time and space becomes important to accurately answer questions about the energy system. Spatial detail may be critically important for renewables: their economic potential and generation costs depend greatly on their location. The much-discussed issue of renewable intermittency, i.e. their variation through time, can be reduced if fluctuations can be balanced by spatial distribution. By influencing the amount of storage needed, this becomes an important driver of system cost (Budischak et al., 2013). The importance of temporal resolution when dealing with significant shares of renewables was shown by Haydt et al. (2011), who found that models which do not consider the full variability of demand and supply fluctuations can overestimate the amount of demand met by fluctuating renewables. When electricity markets are to be depicted in a model, a high temporal resolution is even more important. For instance, recent work found that intuitive effects such as the financial attractiveness of rooftop photovoltaics due to its smoothing of afternoon demand peaks, are not as simple as they seem at first and need to be investigated with high-resolution models (Glassmire et al., 2012).

3.3 Paradigm: Energy system simulation models

In parallel to the bottom-up optimization models, a second important family of large national or regional scale models are based on simulation methods, which instead of generating possible futures, focus on predicting the system's likely evolution. In contrast to the often rigid mathematical formulation of optimization models, these simulation models can be built modularly and incorporate a range of methods (some submodules again incorporating optimization methods). Important examples of this family are NEMS (the U.S. Energy Information Administration's National Energy Modeling System) and PRIMES (a similar model covering the EU). Both NEMS and PRIMES have been in use since the 1990s, which makes them younger than the optimization model lineage.

NEMS is used to produce the Annual Energy Outlook, which helps support decisions in U.S. energy policy. It consists of a number of submodules that are iteratively solved by a central integrating module (Gabriel et al., 2001). Thanks to its architecture, individual submodules can be implemented in different ways, which gives it flexibility, but also makes the system highly complex and can make model results more difficult to understand. Like NEMS, PRIMES is a modular system with an integrating module. The submodules represent independent agents and the model finds an equilibrium solution for energy supply, demand, cross-border energy trade, and emissions in all European countries (E3Mlab, 2008). The PRIMES model has historically been used by the European Commission to provide evidence to support EU energy policy decisions, including analysis underpinning the EU's Energy Roadmap 2050 (European Commission, 2011a).

Another prominent example is LEAP (the Long-range Energy Alternatives Planning System), in use since the late 1980s. LEAP was developed by the Stockholm Environment Institute and is widely used in both the public and private sector (SEI, 2012). At its core it provides a simulation-based accounting system for energy supply with annual timesteps, but it also includes other methods e.g. to represent demand with a macroeconomic model. Its relative flexibility is demonstrated by the fact that its most recent version also includes an optimization component for the power sector, based on the open-source OSeMOSYS model.

3.4 Challenge: Uncertainty and transparency

One can differentiate between two fundamental types of uncertainty relevant to modeling: epistemic and aleatory uncertainty (Kiureghian and Ditlevsen, 2009). To what extent a particular model or model parameter falls into either of these categories is often a decision the modeler has to take: it is epistemic if the modeler thinks that more or better data, or a better model, will reduce uncertainty, and aleatory if uncertainty cannot be reduced further. While there is no way to address epistemic uncertainty (in absence of better data or models), there are formal methods that attempt to deal with aleatory uncertainty. Here one can differentiate between deterministic and stochastic methods for dealing with uncertainty. By applying a deterministic model many times while varying input data (i.e., a Monte Carlo approach), an uncertainty analysis can be performed examining the effects of changes in model inputs on model outputs. A more formal approach is to use a modeling method explicitly designed to deal with uncertainty, such as stochastic programming. Instead of single deterministic values for all parameters, this allows the modeler to specify distributions for some parameters and let the model incorporate that uncertainty into its decisions. Such an approach is taken with the stochastic version of MARKAL, which uses a two-stage stochastic programming method (Kanudia and Loulou, 1998), and by stochastic MESSAGE, (Messner et al., 1996), which formulates the stochastic problem by extending the original linear deterministic problem with nonlinear risk functions. But analyses based on these stochastic models vary only a small subset of parameters based on an analyst's interest or available data, and because of unexpected sources of uncertainty, it may always be necessary to hedge against unknown risks that models cannot predict.

The uncertainty issue can be seen as one aspect of the discussion on whether energy systems models are fit for purpose (Strachan, 2011b). Gilboa et al. (2012) argue that economic models are most usefully seen as describing specific, theoretical systems rather than general rules, and as such, are simply one source of knowledge alongside other data such as experimental or empirical results. This thinking applies to energy systems models: rather than a physically verifiable model, such as the equations describing the theory of gravity, an energy systems model is not verifiable against observable physical phenomena, and should be seen as a source of possible storylines rather than of fundamental truth. The situations modeled by energy systems models cannot be fully observed and measured, and do not exhibit a constancy of structure in time and across variations in conditions not specified in the model; therefore, they cannot be properly validated (DeCarolis et al., 2012).

This issue with validation is what drives some criticism against energy systems models and their use underpinning policy decisions in the UK, EU and beyond (Helm et al., 2003; European Commission, 2011b). Criticism is leveled against energy systems models both because they can be intransparent (i.e., the inner workings of the model are not described in detail) and inaccessible (i.e., analyses are not reproducible because neither model code nor accompanying data are publicly available). In the language of Ravetz (1999), energy systems models are neither certain nor value-free, rather, they are situated in an area where both the decision stakes and the system uncertainties are high. They are therefore examples of post-normal science, which implies seeking a diverse set of opinions, including from non-experts.

The transparency and validation conundrum is related to the key importance of assumptions in models. For example, assumptions made about the load factor of fossil fuel capacity displaced by renewables can be the key factor determining renewable energy costs (Skea et al., 2008). Energy systems models can be seen as methods to examine the implications of assumptions made by the modelers, such as technology costs and performance, economic development, and policies such as carbon pricing. However, if the assumptions are inadequate, then the results will be poor regardless of model choice (Klosterman, 2012). In order to counter criticism about their assumptions (e.g., Helm, 2008), energy systems modelers could increase efforts to publicly release data and models. An important argument is that when insight gained from models is used to design public policy, the models should be transparent and accessible to a degree where independent review is possible. On the other hand, modelers often prefer to invest limited resources in modeling and analysis work rather than in documentation and maintenance of publicly accessible databases. Furthermore, energy systems models often contain proprietary knowledge and commercial data, and represent a large accumulated intellectual capital for their owners. Even the simpler models are complex, and superficial treatment of their complexity by non-experts is desired neither by modelers nor their critics. Yet Ravetz (1999) argues that for post-normal science to succeed, quality is of essence, and this means quality of the process as much as of the outcome.

3.5 Paradigm: Power systems and electricity market models

Further removed from large energy systems models is a set of models that deals with one particular aspect of energy: electricity. Power systems models are traditionally used within utilities and other power sector businesses to make decisions ranging from investment planning to operational strategies such as generator dispatch (Foley et al., 2010). This range of applications can once again be roughly correlated to normative-optimization and predictive-simulation modeling approaches. In general, power systems models are characterized by more detail and attention to temporal variation, since a key element of a functioning power system is a constant balance between supply and demand (Machowski et al., 2011). Electricity market models are related to power systems models, but instead of focusing on physical properties such as power balancing and load on the grid, they concern themselves with increasingly liberalized electricity markets (Ventosa et al., 2005). They thus combine a range of modeling techniques dealing with electricity systems and markets. As electricity increases in importance (Williams et al., 2012), lessons learnt from these fields and the approaches they have developed are becoming more relevant to energy systems modeling as a whole.

Examples of large traditional power systems models include WASP (IAEA, 2001) and PLEXOS (Energy Exemplar, 2013). WASP (Wien Automatic System Planner) is maintained by the International Atomic Energy Agency (IAEA), and was first used in 1973, but remains popular. Its primary purpose is generation expansion planning. It uses a custom dynamic programming algorithm, which is more common in power systems models than the standard solvers used in energy systems models. It can plan several decades into the future, while retaining detailed representation of effects such as unit outages and hydro plant flow constraints. PLEXOS is a mixed-integer linear programming model with detailed modules for various power plants, the transmission grid, and for market planning or capacity expansion. Given the appropriate data it can perform analyses at up to 1-minute resolution, giving high detail on supply and demand fluctuations. Both WASP and PLEXOS are commercial, as are most commonly used large-scale power systems models.

Models specifically analyzing the electricity market have also moved into the area formerly dominated by large energy systems models. One reason is that the variability of renewables plays an important role in determining prices, resulting in changed incentives to build other types of power plants (Traber and Kemfert, 2009). An example of such an electricity market model with aspects of an energy systems model is ELMOD (Leuthold et al., 2012). It is a bottom-up engineering/economic model of the European electricity market which considers 24-hour windows with hourly temporal resolution, and is formulated as a non-linear mathematical programming problem. Its possible uses range from market design to investment decisions.

3.6 Challenge: Complexity and optimization across scales

Krakauer (2013) defines complex systems as ones that "do not yield to compact forms of representation". Indeed, energy systems appear to be examples of such complex systems. The question then arises whether energy systems models are too compact a representation, in other words, whether they may miss some important aspects of the systems they depict either by making trade-offs in resolution or by using simplified assumptions. These are not just theoretical questions, as overoptimized complex systems can harbor risks such as diminishing returns as the overhead of maintaining the system itself grows, and suffer increased vulnerability to unexpected shocks (Fisk and Kerhervé, 2006; Ulanowicz et al., 2009). Energy systems become more complex and interconnected as they grow more decentralized, reliant on more diverse energy sources, and increasingly networked across borders. These growing risks and the realization that some of the current tools are no longer adequate to deal with them have led to calls for a new transdisciplinary power grid science (Brummitt et al., 2013).

The issue of complexity is linked in some important aspects to the issue of scale. Usually, a model is either designed to follow the evolution of an energy system in the long term, with coarse resolution, or to analyze the planning or operation of a system over a shorter period with fine resolution. "Scale", in this context, means the relative size of the boundary of an analyzed or modeled system, so a large-scale model covers an entire continental region with coarse resolution, while a small-scale model covers a single location with high resolution. However, high-resolution phenomena such as demand fluctuations may be important for the long-term system design. Integrating information across these different scales with their appropriate resolution is still a challenge due to associated computational demands, and is an area where the approaches pioneered by interdisciplinary complexity science (Waldrop, 1994) may prove valuable. Instead of defining complex interactions between many parts of a system and simulating the entire system as an integrated whole, the complexity science paradigm is to specify individual parts (agents) in an as simple as possible formulation, then specify the rules they follow and their interactions with the environment. This approach allows decoupling of processes that happen at different scales more easily by specifying agents on different scales and letting them interact.

An example of a model that incorporates such ideas is EMCAS (Electricity Market Complex Adaptive System, Argonne National Laboratory, 2008). The model lets agents interact on five layers: the physical/load flow layer, three market layers (transmission and distribution companies, bilateral contract markets, pool markets), and the regulatory layer (Veselka et al., 2002). This is very different from the central planner with perfect foresight often implied in classic optimization models, and combines bottom-up engineering analysis of load flows with heuristic analysis of economic agents. EMCAS is an example of a growing trend of using agent-based models, particularly in power systems modeling.

3.7 Paradigm: Qualitative and mixed-methods scenarios

Paradoxically, one of the great strengths of large-scale energy systems models (their bottom-up detail of the complexity in the system) is also one of their great weaknesses. The need to capture myriad interactions leads to such complexity in the models that they become intransparent and are therefore criticized as ill-suited for policy analysis. The push for high resolution and technical detail also means that models can take hours or even days to compute one case. Much of the effort in energy systems modeling is to ultimately produce feasible or probable scenarios. Using a heavily quantitative approach is one way to do this, but at the other end of the scale is the combination of qualitative and quantitative approaches all the way to pure qualitative methods (Chermack et al., 2001). This links again to the idea of post-normal science and to models as one type of knowledge amongst others, and thus warrants a discussion of such qualitative and mixed-methods approaches as complementary to quantitative models.

Prominent recent examples of simple but quantitative scenarios are the UK Department for Energy and Climate Change's 2050 pathways (DECC, 2010) and the scenarios constructed by MacKay (2009). The 2050 pathways are based on different combinations of sectoral assessments on what degree of change is technically feasible, and efforts have been made to make them transparent and accessible through downloadable Excel spreadsheets and web applications. Another example, the climate stabilization wedges proposed by Pacala and Socolow (2004), were based on simple calculations about the extent to which different technologies (not limited to energy) could reduce emissions. They combine back-of-the-envelope type quantitative reasoning with qualitative judgements on which wedges to combine in order to achieve a "stabilization triangle" and successfully mitigate climate change, and are thus a useful and accessible way of considering the decarbonization challenge.

3.8 Challenge: Capturing the human dimension

Even these comparatively simple methods focus heavily on technical and economic aspects. However, much of what stands in the way of technology deployment is political will, public acceptance, behavior and the difficulty of changing it. This leads to a final shortcoming, a tendency to focus on factors that lend themselves to modeling (i.e., technological and economic factors), but a relative neglect of factors that may be equally or even more important, such as human behavior, indirect costs, or socio-political and non-financial barriers to deploying technologies. A review in Hughes and Strachan (2010) found that for the UK, there are few low carbon scenarios that take social aspects into account, none with political aspects, and that scenarios with social aspects contain little or no detail on economic and energy aspects.

The fact that these latter factors are poorly understood and scarcely depicted in models contributes to high model uncertainty. The demand for energy and specifically electricity has seen much attention, and this sub-field mirrors issues in the wider energy arena: top-down approaches treating energy users as sinks or considering energy demand rather than energy services demand, and using indicators such as macroeconomic variables on the one side. On the other side, bottom-up approaches estimating individual behavior and needs, and the resulting energy use, then extrapolating from this (Swan and Ugursal, 2009). Addressing energy demand instead of supply is seen as a key component of driving forward a low-carbon energy system (Strbac, 2008). This path is additionally attractive because changing people's behavior is not necessarily subject to the constraints of technology deployment speeds (Kramer and Haigh, 2009). Yet evidence gathered so far suggests it is challenging to achieve lasting change in energy use behavior (Stromback et al., 2011), and many of the proposed demand response strategies do depend on new technologies such as smart meters. Consequently it is difficult to aggregate the insights from such bottom-up research and integrate them into systems models.

On a larger scale, much research has been conducted into the reasons for acceptance or rejection of renewable technologies, for instance wind farms (Toke et al., 2008; Aitken, 2010; Firestone et al., 2012), including quantitative empirical work (Wolsink, 2007). However, there is still the potential for more of this research to be incorporated in energy systems models. An alternative approach to capture this is scenario building focused on non-technical factors. For instance, the transition pathways for a UK low carbon electricity future focus on the role of actors rather than just technical feasibility projections (Foxon, 2013), building on the socio-technical transitions framework developed by Geels (2002). Another example is the Foresight SEMBE (Sustainable Energy Management and the Built Environment) project, where the co-evolution of social, economic, political and technological aspects of the energy system and the built environment are examined together to determine feasible pathways (Rydin et al., 2008). Integrating such diverse approaches in the context of quantitative energy scenarios is a challenge that is yet to be fully tackled.

3.9 Summary

The above section summarizes four modeling paradigms: (1) energy systems optimization models, (2) energy systems simulation models, (3) electricity market and power systems models, and (4) qualitative and mixed-method scenarios. It also lays out four challenges facing energy systems modeling: (1) resolving time and space, (2) balancing uncertainty, transparency and reproducibility, (3) developing methods to address the growing complexity of the energy system, and (4) integrating human behavior and social risks and opportunities. There are of course other important issues and shortcomings in energy systems modeling which this classification does not address, for example, improving how models render technological learning (Kahouli-Brahmi, 2008).

4 Emerging approaches

This section discusses the four challenges in more detail. In addition, it examines current efforts to address them by giving examples of how existing models are being adapted to deal with the challenges, and by describing new models designed to tackle them more effectively.

4.1 Resolving time and space

When energy systems models were initially developed, plants were either baseload (running at all times) or dispatchable at will (able to ramp up or down to match demand as needed). The situation is different today. The first and most important issue is that renewables are variable. The second issue is that some renewable power sources do not provide the same grid services as thermal plants do: stabilization due to generator inertia, and spinning reserve capacity (i.e., dispatchable reserve capacity that can be brought online rapidly in case of unexpected demand peaks).

The first issue can be addressed (in increasing order of data intensity) by using (1) load duration curves or capacity factors, (2) time slices with representative days and seasons, and (3) real time series of solar or wind production potential. Using real time series also helps address the second issue. Haydt et al. (2011), when discussing ways to match power supply with demand, calls these three approaches integral, semi-dynamic and fully dynamic.

MARKAL and MESSAGE would be examples of the integral approach, and only allow fixed time slices. To represent variability, therefore, high-resolution load and renewable resource data can be used to generate additional model constraints (Sullivan et al., 2013). TIMES allows arbitrary time slices. Pina et al. (2011) build a TIMES model with 288 time slices: four seasons, three days per season, and 24 hours per day. This is therefore an example of a semi-dynamic approach with TIMES, but only for an island power system, so it is more a proof of concept than a large-scale application. Even adding more time slices and representative days does not fully address the problem, as it can gloss over correlation between real weather, and miss system-defining extreme points. It is therefore unlikely that the traditional optimization models can fully represent the resolution challenges that come with the energy transition.

Because renewable energy depends on the weather, it is important to have data resolved sufficiently well in space, but also data that corresponds to real weather and its correlation between sites. Combining high spatial detail with high temporal detail brings models to the limits of being solved in reasonable time. For instance, the Regional Energy Deployment System (ReEDS, Short et al., 2009) has high spatial resolution but only uses representative weather conditions over

2-year planing periods. In addition, the difficulty of acquiring high-quality renewable potential data illustrates an important problem with high-resolution models: obtaining data at sufficient resolution and quality but also covering a wide area is difficult, but its lack may mis-represent renewable energy potential by ignoring important detail. For example, wind potential is shaped by local topography, while solar potential is shaped not just by downward radiative flux but, depending on the technology under consideration, the ratio between direct and diffuse irradiance.

Fully dynamic methods, using time series based on measured or modeled climate data, are generally used to analyze single sites before building wind or solar plants, rather than entire energy systems. However, because they solve many limitations plaguing the other methods to fully depict renewable generation, recent work has focused on moving energy systems models towards a fully dynamic approach to entire energy systems for planning and policy purposes, which means emulating some of the methods used in power systems models.

Three examples of this movement are SWITCH, LIMES-EU+, and PowerACE-Europe. SWITCH (Fripp, 2012) is a stochastic linear optimization model that uses average data in each investment period to decide on built capacity. Rather than using full time series, it then takes sample days with hourly resolution for each month to make operational decisions and compute actual electricity costs. The sample days are selected from real data for the year 2004 and each month's samples include that month's peak load day. LIMES-EU+ (Haller et al., 2012b) is a power systems model to perform national-international scale analyses incorporating fluctuations of renewables and their spatial characteristics. It is a linear optimization model with perfect foresight and perfect information. The EU-wide coverage comes at the cost of lower temporal resolution than SWITCH (only 6-hourly time slices). PowerACE-Europe is a linear optimization model that balances electricity supply and demand (including interconnects and storage) at hourly resolution across the EU. It needs to be given installed plant capacities as a parameter, which in Pfluger and Wietschel (2012) is achieved via PowerACE-ResInvest, an agent-based energy investment model discussed below. PowerACE-Europe uses hourly generation profiles calculated from real weather data, so can represent the spatial and temporal weather correlation.

4.2 Addressing uncertainty, accessibility and reproducibility

While enhanced versions of models such as MARKAL and MESSAGE using stochastic programming methods have existed since the 1990s, a renewed interest in uncertainty has led to new work in this area. For example, Usher and Strachan (2012) implement a stochastic version of the UK MARKAL model to examine mid-term uncertainties in the UK energy system. To achieve a computationally feasible stochastic version of the large, computationally intensive UK MARKAL model, the analysis is limited to nine "states of world", meaning that no more than nine discrete future values shared between one or more uncertain variables are possible. This demonstrates the difficulty of extending existing large-scale models to perform extensive uncertainty analyses.

A way around this problem arises from the realization that complex energy models are often no better than simple ones in their predictive power, if prediction is the goal (Klosterman, 2012). Therefore, reducing model complexity to the point where solving a model run takes only seconds instead of hours, allows the modeler to perform rigorous uncertainty and sensitivity analyses on a wide range of parameters. This approach is taken by the Temoa model (Tools for Energy Model Optimization and Analysis, Hunter et al., 2013). Temoa is a linear energy systems optimization model with an open source code base, designed specifically to address the difficulty of performing uncertainty analyses using large-scale energy systems optimization models. Temoa implements a "modeling to generate alternatives" (MGA) approach (DeCarolis, 2011).

MGA is a structured way to explore near-optimal solutions to an optimization problem in order to develop alternatives beyond a single optimum. This follows from the realization that it is impossible to truly address structural uncertainty in a model, and therefore that interesting solutions are likely not to be the single global optimum.

Once an analysis is completed and submitted to a peer-reviewed journal (whether it addresses uncertainty or not), referees are often limited to assess model-based analyses against existing results and their own experience, except where journals have explicit policies that require code and data to be available (Ha-Duong, 2001). Efforts to address this challenge are gaining traction. For example, DeCarolis et al. (2012) lists some steps modelers can take to increase transparency and reproducibility: (1) making source code publicly accessible, (2) making model data publicly accessible, (3) making transparency a design goal, (4) utilizing free software tools, (5) developing test systems for verification exercises, and (6) working towards interoperability among models. Two of the models discussed above, Temoa and SWITCH, are completely open source (although SWITCH still depends on the availability of a commercial optimization framework). A third important example is a reimplementation of a MARKAL-style linear optimization model: the OSeMOSYS model (Open Source Energy Modeling System, Howells et al., 2011). In addition to being fully documented and open source, it is also implemented in the GNU Linear Programming Kit, a free and open subset of the AMPL modeling language. The addition of smart grid elements (Welsch et al., 2012) demonstrates the usefulness of its extensible modular structure.

To summarize, uncertainty in models is being tackled in various ways. One is to extend existing large-scale models by including uncertainty via stochastic modeling. Another is to use new models designed from the ground up to address the challenge. Finally, by making analyses more reproducible and transparent, modelers are also enabling a more informed discussion on the uncertainties and assumptions inherent in complex energy systems models.

4.3 Complexity and optimization across scales

The challenge of resolution in time and space has already been discussed. There is also the related question of scale, that is, about moving from the scale of second-by-second balancing of power supply and demand to that of designing infrastructure with many decades of lifetime and long-term path dependency (see Figure). An alternative approach to simply increasing temporal resolution is therefore to consider different time scales with different levels of detail (Haller et al., 2012a). For instance, many models contain a planning step and an operational step. At the planning time scale, decisions are made about how much capacity to install. At the operational time scale, decisions are made how to operate the available system to satisfy a given energy demand (for example, Fripp, 2012). Such a model could be called a two-scale model. Extending this to more than two scales by the example of continent-wide electricity grid, sensible scales might be local (the generation profile of individual solar or wind sites), national (the characteristics of the national energy system and aggregated demand it needs to match), and international (the capacities for long-range transmission and the additional balancing possibilities this introduces).

A common approach to integrate phenomena happening at lower scales into the topmost scale of a model (e.g. to integrate real-time load balancing constraints into a decade-scale energy systems model) is to use simplified heuristics. However, heuristics do not work well when the exact nature of the effect to be included is not known or has not been examined in detail, which leads to the question of how to explicitly model effects at all scales while maintaining computational tractability (Parpas, 2010). This is a trade-off between stylized models revealing the big picture but reaching wrong conclusions due to their simplifications, and detailed models revealing insight on only a small subset of a system (Brummitt

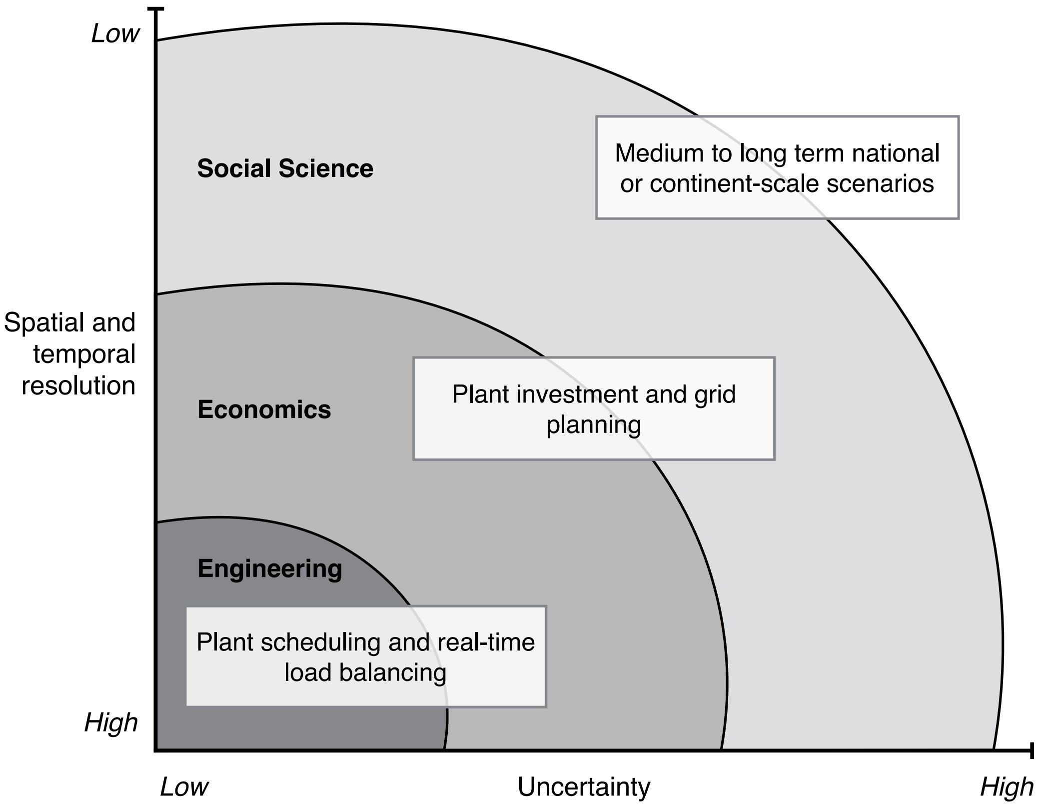

Figure 1: Three stylized scales relevant for energy systems.

et al., 2013), and thus missing opportunities and trade-offs achievable through broader systems integration.

Scale and cross-scale problems appear in many other fields. For example in chemical engineering, Li et al. (2004) characterize three types of multi-scale methods: (1) descriptive ones to distinguish structures at different scales, (2) correlative ones to formulate higher-scale phenomena by analyzing lower-scale mechanisms, and (3) variational ones to reveal the relationship between scales and the mechanisms dominating the overall system structure. In social science, multilevel analysis is an established statistical method used to analyze hierarchical data sets, i.e. data that consists of multiple nested layers (Steenbergen and Jones, 2002). Hierarchical methods for treating different spatial scales represented with different spatial resolutions are also used in climate modeling (e.g., Min and Hense, 2007). Creutzig et al. (2012) propose, in the context of bioenergy models, an approach to reconcile bottom-up models (e.g. life-cycle assessment of bioenergy proposals) and top-down models (e.g. integrated assessment models) into a hierarchical modeling framework. Integrating information from different scales is an important way to address model uncertainty (Lemoine, 2010; Creutzig et al., 2012). In land-use modeling in particular, the scale issue has been recognized and documented (Rindfuss et al., 2004; Evans and Kelley, 2004), and multi-scale models have emerged as a prominent and important method. For instance, Verburg et al. (2008) link together models running at coarse resolution at a large scale with highly resolved models at a local scale.

Instead of linking together models at multiple scales, another approach is to exploit the properties of the problem to simplify its solution in a fully integrated model. For example, Ghosh et al. (2001) describe an adaptive method for multi-scale damage analysis in composite and porous materials. The key feature is that such a method intelligently searches for hotspots using a low-resolution large-scale method and then zooms into these hotspots using a high-resolution small-scale method. Another example is Hagen-Zanker and Jin (2012), who for a spatial economics model propose an adaptive approach to algorithmically decide which geographical zones to cluster together and which ones to keep disaggregated such as to minimize model error. An example of application of such methods to energy systems is Parpas and Webster (2014), who formulate a multi-scale stochastic model for capacity extension planning.

Finally, complex systems research is developing methods to model multi-scale systems in areas ranging from finance (Farmer and Foley, 2009) to ecology (Levin, 1998). One insight arising from this research is that complex systems can exhibit emergent effects driven by the interaction between their constituent parts, and this can lead to sudden and dramatic changes (Scheffer, 2009). An example from the energy area is the large blackout in the Northeastern United States and Canada in August 2003. A combination of factors including one power plant going offline, improper tree maintenance along some transmission lines, and the resulting overloading of other lines, rippled across the system (US-Canada Power System Outage Task Force, 2004). Such effects can be unexpected, in particular if a model of the system does not capture the relevant interaction between parts. A wide range of optimization methods have been used to model energy systems (Baños et al., 2011), but the key methods used by complex systems researchers go beyond optimization. The most important example are agent-based models (ABM), which can capture the interactions between simple agents and simulate the emergent behavior resulting from these interactions. In addition to EMCAS mentioned above, PowerACE-ResInvest (Sensfuß and Ragwitz, 2008) is an interesting example from the energy systems field as it links to a classic optimization model (PowerACE-Europe). It is an investment model including as agents the consumers, renewable generators, utilities and transmission operators, and its design intention was to examine the interaction of the electricity market with renewable energy. There is still much space for such models to play a greater role in the energy systems modeling landscape.

4.4 Human dimension: behavioral and social factors

The relevant human dimensions of energy production and use also vary on different scales. At the very local scale, individual people and households use energy to fulfill their demand for services and products. At a national scale, individuals, communities and organizations shape and steer the adoption of policies and technologies. Public perceptions determine the acceptance of such things as solar panels on roofs and wind turbines on shores and in fields. These factors have long been outside of models, yet play a key role in how the energy system changes. Thus, they are major drivers of model uncertainty.

Modeling often focuses on cost-benefit analysis (in the climate context, what degree of decarbonization is necessary?) and then cost-effectiveness (what mix of measures can best achieve this degree of decarbonization?). However, individuals whose behavior is depicted in an aggregated manner in a model do not necessarily optimize costs. For example, the switch from incandescent light bulbs to energy-saving replacements is driven by regulation and environmental concern, but it is also shaped by personal preferences, not necessarily by cost savings (Veitch et al., 1993). There is a recognition in the literature that there are likely significant untapped possibilities for improvements in efficiency in domestic energy demand (Jamasb and Pollitt, 2011). Flexible power demand is potentially an important part of a future energy system, but it is complex to understand as it depends on both technical and human factors (Pöyry, 2011). Work is progressing on technological, behavioral (individual) and social (cultural/societal) approaches to understanding demand (Higginson et al., 2011). Sociological research provides valuable insight here, for instance, Higginson et al. (2011) describe the benefits of having sociological theory inform an engineering model of flexible demand. Combining technical and behavioral aspects, Richardson et al. (2010) model domestic demand at a 1-minute resolution using a building occupancy and appliance use model, and combine this into an integrated model with rooftop solar photovoltaics (Richardson and Thomson, 2012). However, while such approaches can bring insight into how aggregate demand changes when specific behavior patterns change, it does not yet give any insight into how behavior patterns can or may change. To do so, integrating broader social theory for instance on how societies perceive normality of practices is necessary (e.g., Shove, 2003). When modeling is done to support concrete planning or policy processes, iterating between model-based analysis and stakeholder interaction can help integrate a wider range of information in models (Mirakyan and De Guio, 2013). There is a range of tested approaches to including assessing social aspects of energy systems planning, but more work is needed to integrate them with quantitative modeling (Ribeiro et al., 2011).

At the national and regional or continental scale, analyses primarily focus on energy supply. The analysis to perform an assessment of the potential for an energy technology is usually to move from theoretical, to technical, and finally economic potential (Mercure and Salas, 2012). Strachan (2011a) argues that the sensitivity of models to baseline assumptions means that more attention should be paid to these assumptions, for instance, the difference between a business-as-usual policy baseline (including already adopted climate mitigation policies) and a no policy baseline. Since even where stringent mitigation policies have been adopted, such as in the UK, progress towards interim goals has been far from the required changes (Committee On Climate Change, 2012). Therefore such policy baseline assumptions should also include assessments of how likely it is that policies will be implemented. Some work is emerging on how to quantify the role of the societal actors which come into play, going beyond perfect foresight and rational central planning or rational economic agents with perfect markets. Hughes et al. (2013) use actor-based scenarios to characterize different elements of a future energy system as pre-determined, actor contingent or non-actor contingent. Trutnevyte et al. (2012) use a traditional technical feasibility and cost-effectiveness model approach but develop a whole range of possible scenarios, and include relaxations of cost constraints based on prior interviews demonstrating that people are willing to pay more than what would be cost-optimal. Multi-objective optimization methods allow including quantifiable non-economic factors, but also increase model complexity (Alarcon-Rodriguez et al., 2010). Such approaches are important first steps to include in model-based analyses more of the factors that drive the modeled systems in reality.

4.5 Example of current energy systems modeling in the UK

The UK provides a good example for the trends we describe. The government's enactment of a legally binding 2050 emissions reduction target together with 5-year carbon budgets starting from 2008 have resulted in a need for analysis to support this transformation. The use of models to address the four challenges we identify in the UK is summarized in Figure . The MARKAL/TIMES model family plays an important role in UK energy systems modeling and is being continuously developed. Most recently, work for the UK Department of Energy and Climate Change (Hawkes, 2011) and the UK Energy Research Centre (UKERC, 2013) updated and expanded the UK MARKAL data to better represent new technologies such as renewable energy and flexible demand. Similarly, Dodds and McDowall (Dodds and McDowall, 2013) expanded UK MARKAL with decarbonization options for the gas sector to improve understanding of the future of the country's gas network. Another important recently developed model is ESME (Day, 2013), a linear optimization model to analyze energy technology choices specifically in the UK. It aims to both provide higher spatial detail by resolving regions within the UK, but also has the ability to run and compare a large number of scenarios where some parameters are drawn from a specified random distribution. This is in addition to the continued use of stochastic extensions to existing models, in particular stochastic MARKAL, which has seen recent use in a study commissioned by the government's independent Committee on Climate Change (Usher and Strachan, 2011).

We have described above some examples of models that go beyond global optimization and try to depict complex interactions across scales and market effects, such as EMCAS and PowerACE-ResInvest (Argonne National Laboratory, 2008; Sensfuß and Ragwitz, 2008). We see no examples of such models specifically for the UK yet. Instead, studies have soft-linked existing models to balance their weaknesses. For example, Chaudry et al. (2009) couple three models: MARKAL to analyze the overall energy system, WASP to model electricity generation requirements in more detail, and the spatially explicit Combined Gas and Electricity Networks (CGEN) model to analyze electricity and gas infrastructure requirements. Similarly, although work is happening on better understanding social and political constraints and uncertainties in future energy scenarios, and on integrating these as well as behavioral aspects into energy systems models, no UK-specific modeling work has been published in this area.

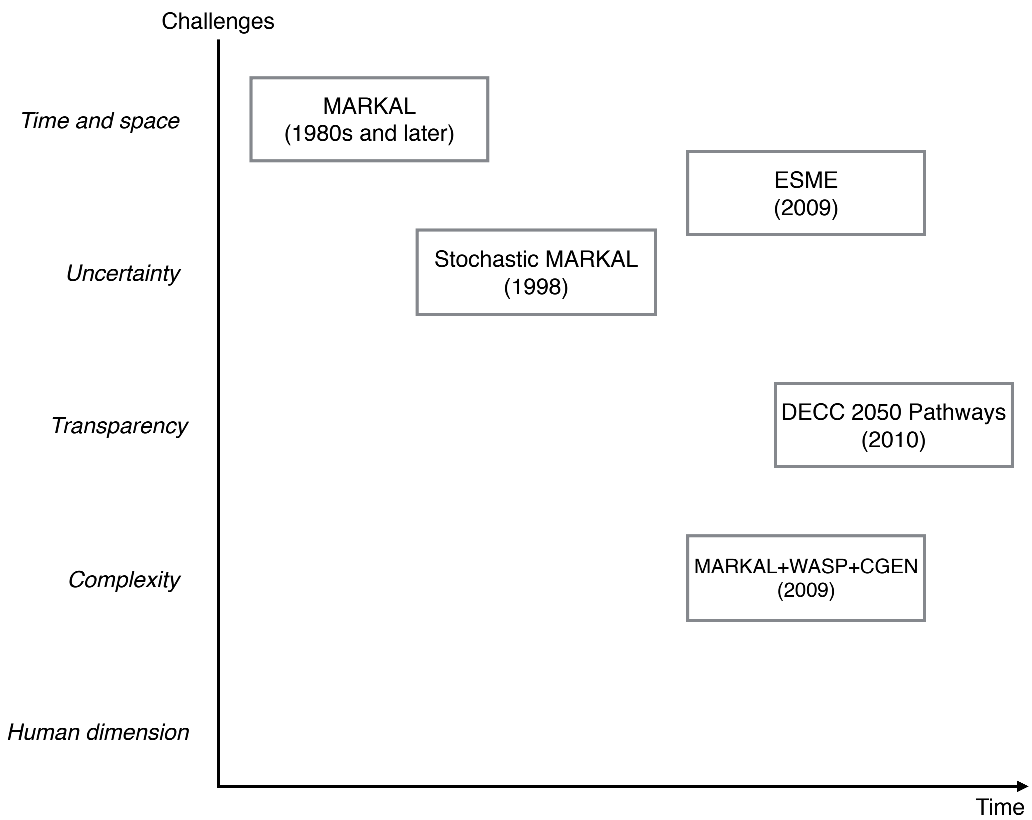

Figure 2: Models used to address the four challenges in the UK.

5 Discussion and conclusion

We have shown how existing models are not always adequate to deal with twenty-first century energy systems, but how they retain an important role and continue to form the basis for much analysis underpinning policy in many countries and regions. We have also highlighted key challenges and how the energy systems modeling community is addressing them, with higher resolution of space and time a particular concern at the moment. To some extent, this challenge in particular overlaps with methodological challenges arising from the economic transitions underway in the energy sector: the liberalization and internationalization of energy markets in general and electricity in particular. The power systems field has many well-established methods to deal with these, and we suggest some convergence between power systems and energy systems modeling is taking place and will be increasingly useful to tackle a more flexible and electricity-dominated energy system.

Several concrete recommendations for modeling emerge. The first is to rethink whether current methods are appropriate for twenty-first century challenges. It is important to have a wide range of tools and methods available and to select from this repository when tackling a specific question. The danger is that proven and established methods gain primacy because of their familiarity. Many of the large models used today have existed since before the advent of modern computing innovations as significant as the internet, and since before the advent of many of the large-scale changes in the energy sector underway in the early twenty-first century. Both the challenges and the tools available to deal with them are being transformed at an accelerating pace, and energy modelers must be careful not to be left behind. While they continue to play an important role, large integrated models capturing every possible detail may give way to frameworks that allow smaller, more nimble models to answer specific questions. The second recommendation is to innovatively combine methods from different sources and from other fields. Many of the challenges that exist in the complex networks of energy systems mirror similar challenges in other fields. The emerging discipline of complexity science is developing methods to address these. The successful application of these methods in energy research has demonstrated the usefulness of the approach, but the need for a deeper and more fundamental treatment of complexity remains with much potential for additional research. This links to the third recommendation: to ensure that the effects of increasing complexity can be captured adequately. Energy systems models emerged initially to analyze and plan a sector of the economy that was of crucial importance for the stability of the overall economy. This fundamental reason why energy systems are modeled has not changed today, but the requirements to capture the relevant effects are changing. While energy modelers have always looked to other disciplines for insight and methods, this is now more important than ever. Disciplines ranging from ecology and finance to neuroscience are working on understanding the nature of complex interactions in large networks, and energy systems modelers can make use of the techniques they develop.

But in addition to these methodological challenges, there are also challenges to the use of models as underpinning policy more generally. To counter criticism about their usefulness, modelers must renew their efforts to work towards a better understanding of uncertainty and towards a balanced approach to transparency and reproducibility. To understand their objects of study, they develop both complex pieces of software and large databases of input and output data. Our forth recommendation is that the lessons learned and working standards developed within the open-source software community, and the software development industry generally, could be used as important sources of best practice here. This includes lessons about the advantages of open code bases, but also, using techniques such as unit testing and integration testing to reduce the likelihood of hard to track errors in complex pieces of software. Fifth, and finally, modelers must also make sure to avoid the trap of modeling what is easily quantifiable rather than what are the essential driving variables of the system. This perhaps is the most difficult challenge, as it questions whether models are useful in providing insight on those issues that truly matter for reaching the policy goals we set. On the one hand, more and more data are becoming available, ranging from detailed pictures of individual behavior to large-scale data on whole economies, reducing some sources of uncertainty. On the other hand, the danger of fitting problems to a procrustean bed of modeling remains, but it is something other fields are also grappling with, so again presents an opportunity for cross-disciplinary learning.

Irrespective of how energy systems modeling further develops, policy-makers and analysts supporting them alike should focus on understanding the assumptions that go into any one particular modeling result. This is fundamental to ensuring that the policy implications drawn are sound. Only then can we use models for insight rather than just numbers. There is always the danger of using models as number generators, and of treating numbers coming from energy systems models as more authoritative than numbers coming from other types of knowledge such as qualitative scenario studies. Falling into this trap neither does justice to the type of insight that modeling can bring to the table, nor to the other sources of relevant knowledge available to inform policy. Nevertheless, the continuing importance of models stems from the fact that they do provide crucial quantitative underpinning to scenarios, and more importantly, structured stories about the future based on an organized exploration of data and assumptions. The ongoing challenge for modelers is to ensure that energy systems modeling can continue to deliver this critical insight.

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