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DOI
10.1016/B978-0-12-818567-4.00029-6

Publication date
2019

Document Version
Final published version

Published in
Energy and Behaviour

CHAPTER

Agent-based modelling of the social dynamics of energy end use

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1 Introduction

Socio-technical complexity is conspicuous in the domain of energy. From day-ahead pricing markets to government policy to end-user behaviour, the energy domain is a manifest of intertwined technical challenges and social factors. This chapter considers agent-based modelling and simulation as a tool for understanding behaviours and for advising policy in the energy domain.

As recognised in many chapters of this book, the 21st century sees energy transition as the pressing driver and consequence of energy technology, policy, and systems in much of the world. The grand challenge around today's energy infrastructures is to reach the energy transition in a timely fashion, while meeting other requirements such as security of supply and affordability (Armaroli and Balzani, 2007).

Energy transition is an example of a multistakeholder *wicked problem* (Rittel and Webber, 1974), characterised by the involvement of a variety of stakeholders and decision makers with conflicting values and interests and diverging ideas for solutions. Even the problem formulation itself is contested and, since cause and effect are intertwined with each other, a clear analytical separation between the problem formulation and the solution is not possible.

The consequences of any decision on wicked problems can be profound, difficult if not impossible to reverse, and may result in lock-ins for future decision making. Consider, for example, the decision to construct or decommission a nuclear power plant. Kwakkel et al. (2016) argue that planning and decision making in wicked problem situations should, therefore, be understood as an argumentative process, where three technical constructors—the problem formulation, a shared understanding of system functioning and how this gives rise to the problem, and the set of promising solutions—emerge gradually through debate among the involved decision makers and stakeholders.

Such a socio-technical systems (STSs) perspective offers a conceptual basis for dealing with wicked problems, grounded in systems science, engineering, social

Energy and Behaviour. https://doi.org/10.1016/B978-0-12-818567-4.00029-6

sciences, and complex adaptive systems thinking. Adopting an STS perspective implies that we understand and model parts of the man-made world as systems composed of two deeply interconnected subsystems: a social network of actors and a physical network of technical artefacts (Van Dam et al., 2013).

Together, these intertwined systems form a complex adaptive system: a multiactor network determines the development, operation, and management of the technical network, which in turn affects the behaviour of the actors buy setting physical boundaries and shaping the dynamics of change. The interactions within and between technical systems are defined by causal relationships which are governed by laws of nature, while the actors in the social system develop intentional relationships, based on habits, norms, formal and informal cultural arrangements, and individual psychological mechanisms and biases, to accomplish their individual goals. At multiple hierarchical levels, the technical network is shaped by the social network and vice versa, with feedback loops running across multiple levels and time scales. These elements and interactions form a self-organising, hierarchical, open system with a multiactor, multilevel, and multiobjective character (Kay, 2002). Fig. 1 presents this in a schematic representation (Chappin and van der Lei, 2014).

Granted this perspective, agent-based modelling (ABM) is a paradigm for simulating the actions and interactions of autonomous heterogeneous agents, which do not need to be perfectly rational or perfectly informed, in order to study the emergent system-level effects of collective agents' behaviour within a certain environment, overtime. As we will discuss in the following section, the agents can represent actors

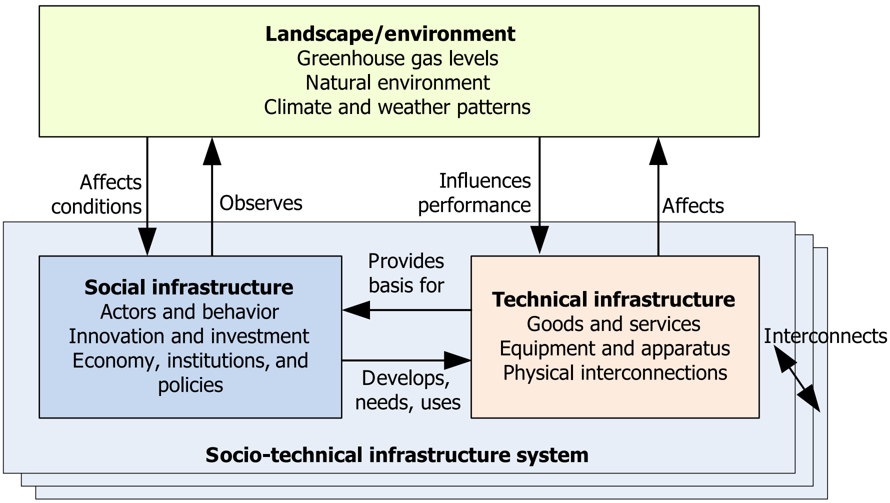

FIG. 1

Socio-technical systems, embedded in a broader ecological system.

From Chappin, E.J.L., van der Lei, T., 2014. Adaptation of interconnected infrastructures to climate change: a socio-technical systems perspective. Util. Policy 31, 10–17.

at different levels of abstraction and hierarchy: for example, individual end users or collective entities such as households or businesses.

The remainder of the chapter is structured as follows. Section 2 introduces more fully the methodology of ABM, placing its methodological approach in the larger STS context. We summarise the steps at a high level in building an ABM, and the challenges and drawbacks of the methodology. Section 3 focuses on the energy domain, and in particular end-user energy use. Section 4 makes the discussion specific by examining three case studies. As a prelude, we point out important considerations when reading a case study of ABM. Section 5 summarises the chapter in the context of the book and points our directions for future research and application of ABM in the energy domain.

2 Agent-based models

Socio-technical systems are defined by simultaneously possessing interrelated social and technical aspects. These interrelated aspects manifest the interaction between human behaviours and relationships, and societal infrastructure and organisational processes. STSs are thus characterised by a set of factors that readily lead to complexity:

- many social and technical components (Hughes, 1987);
- parallel, distributed self-organisation with reflective downward causation (Holland, 1996, 1997; Kauffman, 1993; Kroes, 2009);
- evolution overtime (Dennet, 1996);
- requiring multiple formalisms to understand fully the system (Mikulecky, 2001); and
- loaded with values, emotions, and norms (Funtowicz and Ravetz, 1993; Roeser, 2012; Van den Hoven et al., 2012).

Given the complex nature of STSs, if we are to understand—and further, manage or influence—an STS, then we must be aware of Ashby's Law of Requisite Variety (Ashby, 1991): "A model system or controller can only model or control something to the extent that it has sufficient internal variety to represent it" (Heylighen and Joslyn, 2001). A key term in Ashby's Law is 'sufficient': the expressiveness needed of the model. Note that this needed sufficiency can be defined by the modeller, that is, we can choose a modelling paradigm and design the model with sufficient expressiveness for that which we are modelling.

Nevertheless, 'good' (and 'bad') models come in all shapes and sizes, and should be well positioned in what they do and do not cover. We return to this topic of model quality in Section 4.

When modelling STSs, one can loosely separate the modelling approaches and associated tools into top-down and bottom-up approaches, and across the dimensions of design, analysis, and exploration, as visualised in Fig. 2.

Sitting at one corner point of the figure, agent-based modelling finds itself as a bottom-up approach typically used for analysis and exploration, which, as we shall

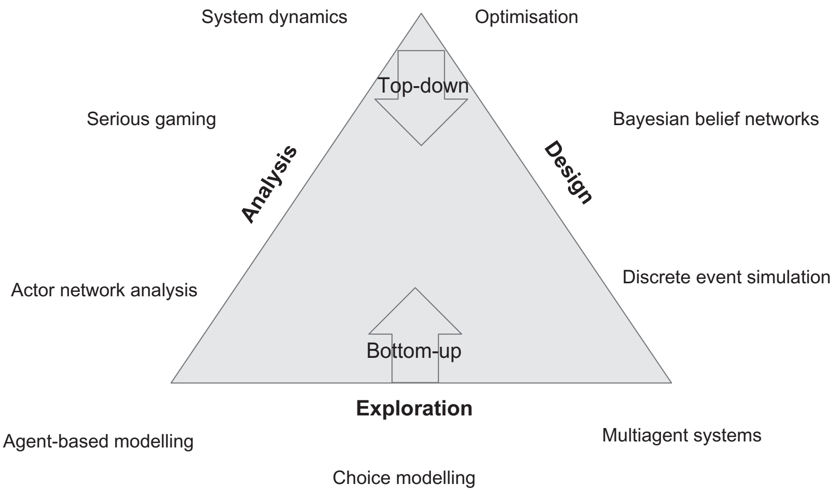

FIG. 2

Dimensions and approaches to modelling STSs.

see, fits its generative nature (Epstein, 1999). At other corners of the figure are multiagent systems (MAS), which we contrast below with ABM in Section 2.1.1; and traditional top-down approaches such as system dynamics and mathematical optimisation. MAS is, like ABM, a bottom-up approach emphasising exploration, but more strongly towards design rather than analysis. Top-down approaches can be used for both analysis and design but are not orientated for exploration, as we discuss in Section 2.1.2.

Anticipating this chapter's discussion of ABM for the energy domain, Table 1 summarises existing approaches for energy scenarios and system models, in studies of energy policy. There is a focus on equilibrium models, in various shapes and forms, which study energy policy questions from the perspective of how they influence the lowest cost/equilibrium solution, either static or under lurching dynamics. The other strand of popular models is system models that study pathways or end states, mostly to find those paths or end states that are assumed to have the lowest system costs. In all these types of models, many of the uncertainties that affect real-world behaviour are ignored or underrepresented. Here, ABM may be complementary, as uncertainties are explicitly studied. Further, elements that do not fit within the economic framing of the modelling are often hard to represent and are typically not in the focus of attention in the modelling practices that have emerged (e.g., see the remainder of the chapter).

2.1 Definition, philosophy, and purposes of agent-based modelling

The modern origins of ABM arise from the work of Conway (1970), Schelling (1971), Axelrod and Hamilton (1981), and Reynolds (1987). Modelling tools became widely available in the 1990s, as the object-oriented paradigm in software development

Table 1 Existing approaches to study energy (and climate) policy.

Element	Computational general equilibrium	Partial equilibrium	Socio-technical energy system models
Time	Equilibrium (static, recursive-dynamic, or dynamic)		Pathway or end state (of least cost)
Scope	Economy as aggregate whole; details for particular sectors	Individual sector in detail	Individual sector with specific technology details
Uncertainty	Some included; in general ignore uncertainties caused by system out of equilibrium, and dynamics from policy uncertainty		

Adapted from Chappin, E.J.L., de Vries, L.J., Richstein, J., Bhaghwat, P., Iychettira, K., Khan, S., 2017a. Simulating climate and energy policy with agent-based modelling: the energy modelling laboratory (EMLab). Environ. Model. Software 96, 421–431.

became more mainstream. Since then, ABM grew as a methodological approach for the social sciences, and evolved into fields such as computational social science and social simulation. Text-books on ABM were written by 2000, and the field had journals and academic societies. For a systematic review and overview, see Bonabeau (2002), Edmonds and Meyer (2013), and Wilensky and Rand (2015).

2.1.1 Different schools of agent-based thinking

Before proceeding further, it is worth recognising that in the broad literature dealing with agent-based perspectives, we can differentiate at least three related, yet distinct schools (besides agent-based methodologies in specific application domains). These schools are:

- AA: Autonomous agents;
- MAS: Multiagent systems; and
- ABM(S): Agent-based modelling (and simulation).

We could understand the AA perspective as asking the *What is?* questions using agents. AA is a part of field of artificial intelligence (AI) field, which itself is a part of computer science. Here, agents are understood as autonomous reasoning and problem-solving entities, and research focuses on representing general reasoning processes in artificial entities. Shoham (1993) provides a background on the AI perspective on agents, and Lee et al. (2014) provide an example of a typical application of agents in AI.

MAS could be understood as asking the *How to?* question. It is related to AA but is closer to engineering in its focus and tools. The goal of MAS is to design distributed control and management systems, that interact, often in real time, with real-world complex systems, such as the electricity grids, traffic control, etc. Čaušević et al. (2017) present a typical example of an MAS applied to managing a decentralised energy production and consumption system.

Finally, ABM(S) could be understood as asking the *What if?* question. This approach is mainly used in engineering and social science fields. Here, agents are understood as relevant and descriptive representations of real-world entities, whose interactions are studied under a range of different conditions to answer questions about consequences of interventions. In this chapter, we focus on this perspective.

2.1.2 Philosophical orientation of ABMs

The mantra of ABM is well expressed by Epstein (1999): "If you did not grow it, you did not explain it!" This expression aligns with questions of interest in social science, where explanation is as important as the 'answer' (Wallach, 2018). Computationally, agent-based models (ABMs) are pattern generators based on state machines, computational devices that systematically simulate interactions of entities overtime, in some environment. The interactions that lead to a new state of an agent and the system are based on the previous agent and system states. Time progresses in discrete steps, and everything within a time step is assumed to happen at once, in parallel.

Unlike traditional modelling techniques which focus on describing the essence of the system, entity, or pattern being modelled, ABMs focus on the essence of the *process* that gives rise to that system, entity, or pattern. Hence, ABMs 'build understanding from the bottom up' we could say.

Western scientific tradition is overwhelmingly based on Aristotle's so-called substance philosophy. Agent-based modelling belong to what can be called *generative science* (Epstein, 1999), which is based on Heraclitus of Ephesus (~560 B.C.E.) and his famous quote 'Panta Rei'—everything flows, the only constant is change. In contrast to substance philosophy, process philosophy thus:

> *…has full systematic scope: its concern is with the dynamic sense of being as becoming or occurrence, the conditions of spatio-temporal existence, the kinds of dynamic entities, the relationship between mind and world, and the realization of values in action.*
>
> **(Seibt, 2017)**

Epstein (1999) goes on to define the central principle of generative science as "phenomena can be described in terms of interconnected networks of (relatively) simple units. Deterministic and finite rules and parameters of natural phenomena interact with each other to generate complex behaviour."

Will Wright, the creator of Sim City (Wright, 1996), which was arguably the first large-scale ABM that entered popular culture, says the following about generative science (O'Reilly, 2006):

> *Science is all about compressing reality to minimal rule sets, but generative creation goes the opposite direction. You look for a combination of the fewest rules that can generate a whole complex world which will always surprise you, yet within a framework that stays recognizable. It's not engineering and design, so much as it is gardening. You plant seeds.*

2.1.3 ABM as a modelling approach

With the earlier understanding of the generative, process-focused philosophy behind ABM, Shalizi (2006) defines an agent and agent-based models as:

> *An agent is a persistent thing which has some state we find worth representing, and which interacts with other agents, mutually modifying each others states. The components of an agent-based model are a collection of agents and their states, the rules governing the interactions of the agents and the environment within which they live.*

Fig. 3 depicts the agents interacting within the environment as an agent-based model.

ABM thus simulates system behaviour as the emergent result of the (inter)actions of situated heterogeneous individuals overtime. This simulated system behaviour makes the ABM methodology very suitable for the analysis of complex adaptive systems such as we find in the energy domain. An agent, its states, its actions, and the environment it 'lives' in are the formalisation of the modeller's simplified, formalised, and (software) codified representation of how an individual perceives the world, thinks, works, and interacts with his or her environment (Fig. 3). It is, therefore, often said that *The agent is the theory*.[a] If the agent is a basis of the generative

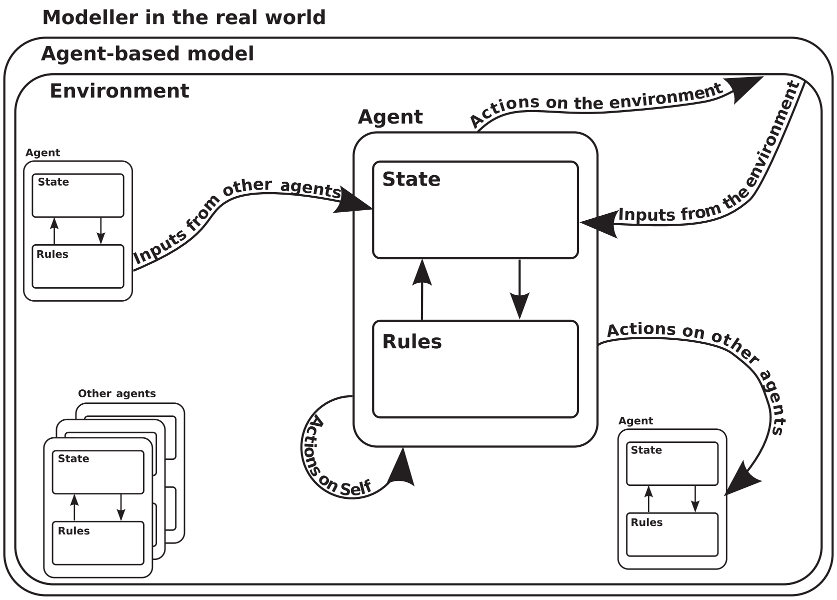

FIG. 3

Agents interact in the environment, in an agent-based model, designed by a modeller.

From Van Dam, K.H., Nikolic, I., Lukszo, Z. (Eds.), 2013. Agent-Based Modelling of Socio-Technical Systems. Springer, Dordrecht.

[a] Saying often attributed to Prof. Nigel Gilbert.

theory, simulated overtime to explore a system's emergent properties, what then are the specific kinds of questions, or purposes, that this tool can be used for? We address purposes of ABM next.

2.1.4 Purposes of ABM

Based on the work of Edmonds (2017) and our experience in the energy domain, we can identify at least six purposes relevant to this chapter.

Theory identification 'Agent is the theory' can more specifically be defined as 'Agent is the hypothesis'. By formalising a particular hypothesis about what an agent is, and how she reasons we can test our generative hypothesis by growing emergent patterns and comparing them with observed reality. A typical example of this type of use is presented by Schelling (1971).

Theoretical exposition ABMs can be thought of as 'a theory with a run button'. If we have a specific theory of the individual in mind, ABMs are excellent tools to present that theory and explore its consequences. As agency is the primary concepts behind ABM, 'things that want to do things to other things', theory exposition done through ABMs can provide intuitive and visual understanding. A typical example is presented by Janssen and Jager (2001).

Explanation When explanation is the main purpose of an ABM, the goal of modelling is to provide a consistent, realistic description of what is going on in a particular situation, regardless whether a description is based on the theoretical concepts, observed heuristics, or empirical data. We are looking for a set of realistic, plausible mechanisms that provide a generative account of the phenomenon. A typical example is presented by Knoeri et al. (2014).

Prediction In situations where the agents' behavioural rules, interactions, and environment are precisely known, ABMs can be used to predict future system states. The most common examples of this type of application are in traffic modelling, pedestrian flow simulations, and evacuation behaviour. A typical example is presented by Hedo and Martínez-Val (2010).

Exploration and discovery As depicted in Fig. 2, ABMs are ultimately suitable for explorative purposes. Asking the 'what if' question amounts to running a model repeatedly under (a large number of) varying initial conditions, parametrisations and external scenarios, and mapping out the space of outcomes. We observe changes in outcomes across the parameter space, and from these changes infer insights about the effects of interventions upon it. A typical example is presented by Richstein et al. (2015).

2.2 Methodology and caveats of agent-based modelling

In this section, we outline a suggested methodology of how to build an agent-based model, and we point out caveats that are important when designing ABMs for domains such as energy and climate.

2.2.1 ABM development process

In the following section, we present an extended model development process, based on the method presented by Van Dam et al. (2013), consisting of 11 steps. The method follows a usual software modelling cycle, adapted to the needs of ABM and the participatory stakeholder involvement. The steps are presented as higher-level questions that need to be addressed during each step, rather than a procedural description of these steps. Note the nuance in vocabulary: actors are the real-world entities involved with the system we are studying, and agents are model representations of actors.

Step 1: Problem formulation and actor identification

The main question here is: *What is the problem?* It leads to clarifying questions, such as *What is the exact lack of insight that we are addressing?*, *What is the observed emergent pattern of interest to us?*, *Is there a desired emergent pattern, and if so, how is it different from the observed emergent pattern?*, and *What is the initial hypothesis on how the emergent patterns emerge, or, why do the observed and desired emergent patterns differ?* Once the problem to be addressed is clarified, the social dimension of the problem field needs to be identified. Questions we, as modellers, can ask are: *Whose problem are we addressing?*, *Which other actors are involved in this problem?*, and finally, *What is our role?*

Step 2: System identification and decomposition

Once the lack of insight has been formulated, we can start to systematically define the system boundaries and the relevant level of abstraction and detail within those boundaries. The questions relevant here are: *Who is there, that affects the emergent pattern?* This questions identifies the relevant agents, based on relevant real-world actors. *What do they know or have?* identifies the relevant states and properties of the agents. *What is here, and is being acted upon by the relevant actors in the system?* This identifies the model objects, the technical components of the system. *What do these actors and objects do?* identifies the actions that agents take upon themselves, others, environment and the objects. The question of *How are these actions performed?* will be asked in step 4. The question *What is the nature of these actions?* identifies the types of flows and exchanges between agents, being money, information, influence, etc. Finally, the two question defining the agents' environment need to be asked. *What are the relevant things/properties of the world that all actors know about or have access to, but does not belong to any of them?* defines the environment. *What are all the relevant things that affect the actors and objects, but are considered too large and too far away to be affected by them, but do affect them?* identifies the system boundaries and determines the exogenous model variables and dynamics.

Step 3: Concept formalisation

In this step, the qualitatively defined agents, objects, their states and properties, actions, the environment, and the external world are formalised in a computational form. The are two main question to be asked here. First, *Is the formalisation commensurable to the involved stakeholders?* If the stakeholder cannot recognise or relate to the formalised concepts, model loses its authoritativeness from the get go. The second question is *Will this formalisation be practical for the kinds of actions and behaviours that we need to describe?* As ABMs are at one level 'just algorithms', choices for data structures have a large impact on the algorithm (and thus the model narrative) used.

Step 4: Model formalisation

At this step, the question asked is, if we will: *The agent wakes up in the morning, has a cup of coffee and does…?* This step explicitly defines the detailed narrative of each agents 'theory', thus answering the question *Who does what, with whom, when, and how?* All agents, objects, their states, environmental components, and the external world must be included in this narrative. This step is the final model design step that can be communicated in practice with stakeholders, before the modeller descends into software development details. It is therefore essential that this narrative is fully understood, internalised and accepted by the stakeholder, because all interpretation of model outcomes and the use of the model will be based on their mental model of this narrative.

Step 5: Software implementation

In this step, no specific question is asked, rather, the narrative is converted into a software artefact. As example of this process for an ABM in energy domain is Eppstein et al. (2011). There are a number of popular software tools used to develop agents-based models, such as NetLogo (Wilensky, 1999), RePast (North et al., 2013), GAMA (Taillandier et al., 2010), MASON (Luke et al., 2004), and SWARM (Terna et al., 1998). The tools differ in their topic focus, intended user group, programming language, user licence, etc. Elaborating on these differences falls outside the scope of this chapter. An up-to-date overview can be found at the Wikipedia page: https://en.wikipedia.org/wiki/Comparison_of_agent-based_modeling_software.

Step 6: Model verification

The main guiding question at this step is *Have we built the thing right?* Like software development meant for products, where the specific implementation details are not important to the end user (as long as software performs the required functions), we do specifically care about how the agent performs its decision-making processes and actions/interactions. In this step, we are building an evidence file on the correctness of the artefact's construction, so that we can have confidence in its outputs when we start using it.

Step 7: Model parametrisation

Now that we have confidence on the suitability of the model artefact for its purpose of generating emergent patterns from theories of individuals and their actions, the question that we face is *What are the right inputs?* There are two questions hidden behind the notion of inputs. First, *What is the state of the world, agents, the properties, and objects that is relevant to the problem?* Based on and limited by the formalisation choices, we need to translate real-world properties into parameter values for the model. The second question is *What else could the world be, and what would we like to do to it?* This identifies the parameter space within which alternative but relevant situations can be represented, and the scenario space, a set of possible states and dynamics of exogenous parameters, under which we wish to explore the model behaviour.

Step 8: Experimentation

Guiding question for the experimentation is *How do I run this thing?* How do we translate the lack of insight defined in step 1 into computational experiments that can generate emergent patterns that can provide that insight. A wealth of detailed choices have to be made, from the how to sample and explore the parameter and scenario space, how to get significant outcomes, given the inherent stochasticity of ABMs, how long to run the simulations in order to get the emergent pattern of interest and do we have the computational resources to perform these simulations. If not, how can we reduce the number of experiments while maintaining their usefulness.

Step 9: Data analysis

What happened? is the main question driving the analysis of the model outputs. It consists of two subquestions. First is *What is interesting?* and the second is *How to show it?*, and both are surprisingly nontrivial. What is a relevant emergent pattern arising from the generative process of agent interactions? Is the absence of a pattern that is interesting? When does it appear/disappear? Which pars of the parameter and scenario spaces lead to these patterns? Is the actual patter/the absence of pattern interesting, or is the difference between two parts of the parameter/scenario space interesting? The second question on visualisation is about identifying the most suitable way to represent an often highly dimensional datasets to a stakeholder in a way that it usefully relates to the lack of insight and their understanding of the model narrative. Data visualisation is a specialised field, and discussing the various options, considerations, and tools falls outside the scope of this work.

Step 10: Model validation

The guiding question behind validation is *Did we build the right thing?* Model validation is a process that is very well understood in the natural science. A model, based on the representation of laws of nature is constructed, it provides a prediction, which is then checked by empirical observation. In the case of socio-technical models, and especially in participatory setting where questions are asked about possible futures states, classical validation is not possible. This is exacerbated by the fact that, in cases where the ABM contains a description of the stakeholder, any model output may change the stakeholder and this renders the model invalid. Several alternative ways of validation are available and will be discussed in Section 2.2.3.

Step 11: Model use

The driving question for the final step is *What can I do with this?* and *How useful is it?* The model outcomes may corroborate or conflict the stakeholders intuitive understanding of the problem at hand. By comparing model outcomes with their own mental models and reasoning about the reality based on these differences, insight about the problem is gained. Whether this is useful, is completely observer dependent and subjective to the stakeholder. It is often reported by the stakeholders that the modelling process was highly insightful, sometimes more that the model outcomes themselves.[b] The model can in that case be considered to be useful, even when incomplete or coarse, as it has provided insights that would not be possible otherwise. It is often said that the usefulness of the model is measured by the speed with it is replaced: a model that is quickly abandoned and replaced with a new one is useful as it has provided so much insight and understanding that it makes its own limitations obvious, and drives the desire for a more complete insight.

2.2.2 Problem-driven strategy to agent-based models

A key strategy for developing an ABM—or any other model for that matter—is to put primary focus into formulating the problem that is addressed, and for that problem, argue how modelling can actually contribute insights towards a solution for that problem. This strategy is particularly relevant for the energy domain. Focusing on the problem and insights from its modelling is particularly relevant for ABM, because of the large number of possibilities in model purposes, in conceptualisation, in implementation, and in experimentation. Complementary, being explicit about the modelling purpose helps to identify the way in which modelling helps in solving the problem. For example, does the model help clarify the arguments, perform a complicated calculation, find problematic conditions, etc. Altogether, the modelling process may be as relevant as the model outcome. In the end, the reasoning of findings that stem from a modelling study should be robust enough to stand alone, irrespective of the model they lead to.

It is also important to acknowledge that good modelling does not often come from a linear approach: following one step at a time. Indeed modelling can help in the creative process by exploring possible ideas, explicating an intuition, as well as in the justification and underpinning of a particular reasoning. The only risk is mixing up these perspectives.

2.2.3 Challenges to agent-based models

As any other modelling approach, ABMs have a number of challenges associate with their creation and use. We will not discuss generic challenges faced by all simulation models, but will solely focus on those specific to agent-based modelling. These challenges stem from:

- the types of data required;
- the algorithmic nature; and
- the types of use

that are typical for ABMs in the energy domain.

Types of data required

For creating ABMs, two key types of inputs are needed. The first is theories or heuristics describing agents, and their behaviours; the second is facts parameterising those agents their behaviours and the environment.

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[b] This is the personal experience of the authors when working on ABMs for various topics in the energy domain.

ABMs of STSs obviously must contain knowledge and facts from social sciences. A given in social science is the 'incoherency problem': the lack of a single fundamental understanding of what motivates human beings to cooperate and what their capacities are (Watts, 2017, p. 1). Natural sciences have a basic unifying ontology, the laws of nature, that are universally applicable and transferable across all natural science domains. Therefore, there can never be a universally accepted and objective choice for which theory of the individual must be used. Do we approach it from the sociological or psychological perspective? Or maybe an economic base for agent description is more suitable? What would the outcomes have been if we had chosen a completely different one over other? This leads to explicit structural uncertainty in ABMs, which may be difficult to systematically explore, both due to effort required to conceptualise multiple agents, thus creating effectively different models, and can be very computationally expensive. There is no closed-form solution here other than being very explicit in the choices made and transparent and systematic in describing the reasons behind those choices.

What about the facts describing the agents? As data are needed at a very disaggregate individual level, it is often either not available, or sufficiently sensitive that it may not be used due to individual privacy or industrial trade secrets or intellectual property issues. Some ways to deal with this is to sample from stochastic distributions describing the individuals data, in case where a large population is involved. If a single, or very few individuals are modelled, where it is clear who that party is, even when anonymised, once can resort to asking the stakeholder to provide data which have been modified with unknown random noise. For example, this situation occurs when modelling production facilities, such as oil refinery, where the specific operational parameters and product composition are highly sensitive, but the general information is not, as all refineries are very similar to each other.

Finally, we can create fact free, but knowledge-rich models. Here, we either randomly assign values to the parameters, or use a best guess method for describing 'reality'. This shifts the burden from data gathering to large uncertainty exploration. In some use cases, this is sufficient for the purpose, such as when we are doing theory identification.

Algorithmic nature

ABMs attempt to describe the parallel, instantaneous actions, and agents' interaction in some environment. We are, therefore, simulating parallel action in a serial processing computer. Even when we have access to heavily multiprocessing machines, there are limits to how much parallelism can be put into the model, even when we ignore the very significant effort in creating scalable parallel processing algorithms. As we simulate time steps, which all agents are assumed to act in parallel, we constantly have to randomise the iteration order of our simulated agents, in order to avoid first mover artefacts. For example, if there is a scarce supply of a good that all agents want to have, if at each time step that same agent gets to buy first, we would severely distort the model outcomes. As agents actions are iterated every step, and their states and actions almost always depend on the previous states and actions, we necessarily have a chaotic system. Chaotic systems are highly sensitive to initial conditions, and a random selection of the iteration order at the first step may be sufficient to produce unstable final outcomes.

This means that model analysis always has to be performed on an ensemble of model runs at identical parameter settings, and outcomes must include a statistical analysis of that ensemble. Luckily, chaotic systems have robust attractors (regardless whether they are stable, unstable, or metastable) and many techniques from dynamical systems mathematics exist to identify and analyse those attractors. This of course involves more effort than a linear model would require and makes model outcomes more difficult to communicate.

Types of use

ABMs, certainly in the energy domain, are usually used for 'what if' scenario exploration types of questions. As is often observed, 'Prediction is difficult, especially if it's about the future'. This truism is especially the case when exploring potential futures of complex, adaptive STSs, whose evolutionary paths are intractable. Further, as already mentioned, STSs only have limited physical science components for which predictable laws of nature hold true. To make matters worse, an agent-based model often contains behavioural models of the involved stakeholder. As the stakeholder uses the model to understand possible futures, her behaviours will change due to this knowledge, however, slightly. In a chaotic, evolving reality this loop—strictly speaking—necessarily invalidates the model, since it changes the agents' state and behaviour.

Further, since many model users are still unfamiliar with notions of emergence, self-organisation, chaos, and notions of generative science, and therefore, tend to expect 'single truths' as model outcomes (Hiteva et al., 2018), ABMs may face issues with model authoritativeness and acceptance of its outcomes.

3 Applying ABM to the energy domain

This section brings together agent-based modelling and the problems in the energy domain. We first identify distinguishing aspects of the domain, discuss, energy-related behaviour, the uptake of energy technology, perceptions, and expectations, interconnectedness, and then consider data, and finally purpose and validation in connection with policy.

3.1 Aspects of the energy domain

In Section 1, we saw the grand challenge around today's energy infrastructures is to reach the energy transition in a timely fashion, while meeting other requirements such as security of supply and affordability (Armaroli and Balzani, 2007). Meeting this challenge requires producing energy carriers from renewable resources, reducing the carbon emissions, and lowering energy demand.

Energy infrastructures provide the service of connecting energy suppliers and users, with the purpose of providing access to affordable, clean energy, with a secure supply. The various energy carriers that each require their own infrastructure; indeed, energy infrastructure is the basis for many of the functions of today's society: health, economy, transport, information technology, etc. Because of its capital-intensive nature, energy infrastructures emerged and evolved over decades and a broad set of actors with different roles, rules—but also markets and policies—has emerged. Any technology, device, fuel, or system is regulated in one way or another, for example, through taxes, tax reliefs, subsidies, concession restrictions, voluntary sector agreements, information instruments, bans, and many of these policies interact across timescales and borders. Altogether we see a complex multi-stakeholder system.

The standard framework for users in liberalised energy markets is a freedom to choose suppliers and a basic right to affordable energy. Nevertheless, climate goals have also translated into policy targets on the user side, in terms of energy efficiency (lowering energy consumption for the same functionality), lowering energy demand, shifting energy demand in order match supply (i.e., demand response), and increasing local energy production [e.g., solar photovoltaic (PV)]. The question is what policies, institutions, markets, and market conditions we need in order to meet the policy objectives. ABM fits well with studying all these user-related processes, since agent-based models can explicitly study under what conditions we may reach our policy targets.

3.2 Studying energy-related behaviour

Many of the relevant aspects of study in the energy domain translate into examining behaviour: simulating end users and their decisions. ABM can explicitly study the consequences of behavioural barriers and policies that may help to overcome them (Hesselink and Chappin, 2019): structural barriers (e.g., split incentives), economic barriers (e.g., lack of capital), behavioural barriers (e.g., bounded rationality), and social behavioural barriers (e.g., lack of trust). Related to but distinct from the study of end-user behaviours, Chapter 2.3 addresses barriers to energy transition in industry.

The barriers identified earlier have been shown to have large effects on why particular energy efficiency objectives were not met; indeed, the barriers are often the reason why particular policies are developed (Hesselink and Chappin, 2019). ABM can, in theory, explore all of these barriers for the energy domain. However, it is often the case that the barriers themselves are not explicitly studied with the models used to develop the policies, whether ABM or other types of models.

Further, the fact that there are so many different barriers, but also end-user groups, appliance types, etc. has led to a large variety of policies, often very detailed. Think for instance of the detailed discussions on energy labels and how they are revised. Because policies interact with each other, much needs to be considered in order to develop specific, coherent, and feasible policy advice.

In the context of liberalised markets, policies are often developed to move end users away from habit-driven behaviour, and towards developing more reasoned actions. A key example is in-home displays and smart meters, which, if supported by policies, inform people on their energy demand with the aim to induce more energy-efficient practices. Other decisions are characterised by the frequency in which they are considered. For instance, heating systems are capital intensive and only replaced infrequently. In particular, many noneconomic factors play a role in those decisions, for instance who's advice is followed and what infrastructure is available there.

Agent's behaviour, formalised as decision rules, may incorporate many of the factors involved with empirical data, in the form of utility functions. Although these utility functions may be heterogeneous and may be placed in a dynamic context of a simulation of interacting agents, the well-known limitations of utility functions still apply (Aleskerov and Monjardet, 2002).

3.3 Exploring the uptake of new energy technology

A purpose for which ABM is well suited is the study of the uptake of new technology, that is, the development of new types of demand and the adoption of new technologies for existing demand (Chappin et al., 2017b). What, for example, may we expect from demand-side management? In order for security of electricity supply, will end users accept giving up some of their autonomy? How can they be persuaded to participate in such a scheme? What infrastructure is needed? These are questions that can be explicitly explored with ABM. It requires an explicit understanding of people behaviour in their homes and the way they decide on their energy contracts, including the terms for financial renumeration (Vasiljevska et al., 2017).

A highly relevant example is how we change the (residential) heating infrastructure in the coming decades, so that sustainable energy sources are used for heating. In the Netherlands, for example, the decision has been made to replace natural gas. But there are many alternatives, and it is a wicked multiactor design problem to explore what technology would work where (heat pumps, district heating, biogas, full electric, etc.), with many fundamental uncertainties, and distributed decision making.

3.4 Understanding perceptions and expectations

Related to behaviour of end users adopting energy technologies, is often the perceptions and expectations of people have about those technologies, which is a key source for policies. The perception that resulted from the performance of energy-saving bulbs from the 1980s and 1990s affected the adoption since and led to a ban on incandescent and halogen bulbs in the European Union (see Chapter 4.3 for discussion). The undeniable factor that perceptions played here has been shown very explicitly with ABM (Chappin and Afman, 2013).

Similarly, expectations play a huge role in decisions in which significant uncertainties may be involved. A prominent example is how uncertainties in future CO_2

prices have been ignored in most modelling studies (Chappin et al., 2017a), where the expectations have affected the value of waiting (delaying the decisions to invest significantly beyond modelled expectations). These processes are explicitly studied with ABM and lead to unique insight in policy side effects and robustness (Chappin et al., 2017a).

3.5 Accounting for interconnectedness

The energy transition drives new interconnections between what were, in the past, separated services. For example, electric mobility interconnects energy, transport, and IT. If electric vehicles (EVs) penetrate the market, they create significant demand for electricity, which, depending on how it will be organised in contracts or regulated, may alter significantly the demand profile for households. Electric mobility is, therefore, a topic that is much broader than the adoption of EVs alone: it also involves design of new roles, new infrastructure, and question about what EV owners will find acceptable. ABM can study hypothetical arrangements of all these interconnections. As a second example, the so-called 'smart' infrastructures accompanied by 'smart' contracts are a means to balance energy demand and supply. These require interconnections with information infrastructures. Again, ABM can study the interconnections.

A second form of interconnectedness is, as we saw earlier, that energy is instrumental for many of today's societal functions. The consequence is that many energy-related decisions are habit driven or are dominated by other aspects than energy itself. This is vital for understanding energy-related behaviour and also for simulating it. It also provides key levers: how can we get end users out of their habit-driven behaviour and into a more reasoned type of action? This suggests the usefulness of in-home displays, smart meters and also of home automation, which essentially bypasses the habit-driven decisions by households. Questions to all these aspects can be simulated and explored with ABM, and the performance policies stimulating particular behaviour may be tested.

A third form of interconnectedness is that households are known to observe and influence each other in their decisions—and this can affect energy behaviour significantly. This influence differs for various appliances and functions: think of the visibility of cars in streets versus light bulbs in homes. For ABM, it is typical to use a constructed social network between agents and agents taking into account properties, opinions of others in their network in their own decisions.

3.6 Inputs (aka 'Data')

The data that goes into ABMs are a combination of data on rules, algorithms, and/or heuristics on how people make the particular decisions which are being modelled, as well as the parameters or properties that go into such decisions.

In order to structure the model of the agents' reasoning and decision-making algorithms, theory may be used. A review on energy efficiency models showed the popularity of the theory of planned behaviour, and of utility theory (Hesselink and Chappin, 2019). The theory employed gives a frame for what kind of data needs to be gathered. The agent-based modelling paradigm enables enormous flexibility in terms of theory and how particular theory can be operationalised. This flexibility has consequences for validation, but also for the data that needs to be gathered. For many elements of modelling the decision making of end users, there is no data and no accepted way of gathering it. For instance, how to get a representative sample of perceptions on brands, technologies, etc.

The data needed for ABM of energy end users include household preferences (which may well be rather specific to location, and particular decisions). In addition, some form of infrastructure data may be needed to be able to describe neighbourhoods and interactions adequately. There are many challenging aspects in collecting the appropriate data: if we think about agent interactions, for example, how do we find out how many people in the network to ask/observe? To what extent does it differ between households?

It is known that small differences may have large effects in complex systems; hence, errors in data could have large consequences. It is a challenge, but also a necessity, to systematically evaluate the sensitivity of a simulation model to possible errors (Van Dam et al., 2013).

Lastly, depending on the modelling scope, national statistics (e.g., census data) may be useful. A key challenge may be to disaggregate data into properties of individual agents. Therefore, such data may be more useful for validation tests than as inputs.

3.7 Purpose and validation

Validation of agent-based models is a particularly challenging task for ABMs of energy behaviour. This is not only because many aspects of 'the system' are relevant, but also because of the forward-looking nature of the questions we have. In the context of energy behaviour, the hypothesis is that if we anticipate the effects of policy decisions with proper use of agent-based modelling, we may be able to improve those policy decisions and influence the efficiency and effectiveness of the energy transition. This implies the need to impact the 'problem owner'.

Considering the role of the problem owner in relation to the purpose of the modelling study, agent-based models have the potential to be developed in participation with, or in close contact with, stakeholders. If energy policy makers, for instance, are involved in the model development process, they may be drawn into the 'way of thinking' with ABM (Section 2.1): how do individuals make their energy-related decisions and how may policy makers influence them efficiently and effectively? This process is less strong if the policy maker is less involved, or not involved at all.

More generally, how insights from models, such as ABM, can aid policy debates around wicked problems is the subject of the literature on the science-policy interface. The importance and challenge of this interface is summarised, for instance, by Watson (2005). Assessing the interface in practice, Brugnach et al. (2007) conclude that "the integration of information derived from models into policy is far away from being trivial or the norm. Part of the difficulties of this integration is rooted in the lack of confidence policy makers have on the incorporation of modelling information into policy formulation." These authors go on to pinpoint as critical factors how uncertainty is modelled and how the model is communicated to the public.

Going further, and writing a decade later, Strachan et al. (2016) find a similar disconnect between models, model outcomes, policy makers, and policy. The authors identify what they call 'short comings' of current practice in modelling in the energy domain: "Policy makers continue to struggle to assess insights from competing models that give alternative findings, or respond when different commentators interpret results to support their arguments."

This relates to the issue of model validity. When validation is defined as fit for purpose, it becomes unfeasible to consider traditional criterion of validity of predictive capability: predictions can never be verified. But in particular, if prediction is not the purpose in the first place, this particular test does not make sense. This important point relates strongly to the difficulties of gathering the right kinds of data, as we discussed earlier.

Although some other modelling approaches (besides ABM) are intended for prediction (recall Fig. 2), the question is whether they succeed at doing so (Chappin, 2018). Energy scenario studies are often supported by models that calculate lowest-cost pathways (Chappin et al., 2017a), which are 'validated' by default because the lowest-cost solution is guaranteed in the modelling method. In addition, models of physical energy systems may be validated in the traditional sense, as they are rooted in laws of physics and there are many known validation tests from electrical engineering. However, the challenge for the energy domain is not only to find lowest-cost solutions (the what?), but what policies may be needed to get there (the how?). In other words, when the scope increases to include social aspects, behaviour, policy, and—in particular with longer time scales—transition, no real validation data are available. Paradoxically, it is that in this wider context, prediction is perceived to be quite important (Chappin, 2018).

Designers of ABMs need to consider the purpose of the model carefully (Section 2.1.4), and 'users' of the modelling work (e.g., modeller, reviewer, policy maker, and colleague) need to be confident that the model fits to this purpose, in terms of (1) what is in the model and what is not for the purpose defined, (2) whether the way in which components are modelled make sense given that purpose, and (3) whether the outcomes can be understood, given those assumptions. If these three points are met and the purpose is useful for the energy domain, then the modelling results can be useful in the discussion around energy policy, understanding energy behaviour, and hopefully, accelerating the energy transition.

4 Case studies

This section looks in detail at three case studies of ABM in the energy domain: energy efficiency in domestic heating; EV adoption; and energy management in smart grids.

First, picking up the discussion with which we concluded the last section, we take the opportunity to reflect on *how* to approach a case study of ABM and the questions to ask about it. We divide these questions into two categories: the model and its use.

Regarding the agent-based model itself: Does the model have

- a clear modelling problem statement?
- a clear definitions of agents, their states, interactions, and the environment?
- a logical and relevant narrative?
- a clear choice for 'KISS' or 'KIDS' methodologies and approach to data (Edmonds and Moss, 2004)?
- sufficient heterogeneity and adequate freedom for agents to act?
- only stochastic decision making by agents?
- a clearly stated list of assumptions?
- any hard-coded choices for parameters only due to expediency?
- behavioural elements whose only justification is that they are easy to model?
- an explicit verification presented (Van Dam et al., 2013, Chapter 3)?

Regarding the use of the model: Does the model have

- a clear rationale for decision on parametrisation?
- a clear rationale why computational experiments are carried out, and under which conditions?
- multiple simulation runs performed?
- descriptive statistics of the outcomes?
- outcomes that are used to reason about reality?
- outcomes that are unwarrantedly used as prediction?
- an explicit statements about limitations?
- an explicit guide to interpretation of the results?

4.1 Energy efficiency

Our first case study reviews 23 agent-based models of energy efficiency (Hesselink and Chappin, 2019). We discuss this paper in this section.

One of the formulated energy goals, for instance in Europe, is to improve energy efficiency. A document from the European Union defines as follows: "Technically, 'energy efficiency' means using less energy inputs while maintaining an equivalent level of economic activity or service; 'energy saving' is a broader concept that also includes consumption reduction through behaviour change or decreased economic activity" (European Commission, 2011). This differs from other key policy objectives (e.g., how the energy input is supplied, i.e., with renewables). It has been shown that energy efficiency targets set at national and international levels are difficult to achieve, despite the fact that there are many energy efficiency policies in place. The potential added value of ABM here is to explicitly simulate the effects of policies through decisions of individuals. In this context, many of the aspects of the energy domain we noted in Section 3 are relevant and studied explicitly.

This case study describes the ongoing efforts in studying energy efficiency with ABM. Although energy efficiency applies both to small and large end users—households and small and large enterprises—Hesselink and Chappin (2019) focus on households.

The energy behaviour dimensions studied include the response of agents to policies, specific to particular types of devices, given various behavioural barriers, as explained in detail here.

4.1.1 Appliances

The following types of appliances have been studied with ABM in relation to energy efficiency: lighting technologies [incandescent, light emitting diode (LED), compact fluorescent lamp (CFL), halogen], residential heating systems [direct electric heating, wood pellet heating stoves, heat pump, aircon, micro-combined heat and power (CHP)], wall insulation, solar PV systems, EVs, CO_2 emission measurement devices, and behaviour changing feedback devices.

4.1.2 Barriers and policies

In the literature, many barriers for energy efficiency have been identified in a variety of studies and many energy efficiency policies have been proposed. Only a rather small set of the barriers have, to date, been explicitly modelled with ABM, and here is a huge opportunity because, in principle, ABM could simulate all of the barriers identified. The same holds for the possible energy efficiency policies. Fig. 4 illustrates which barriers have been studied.

4.1.3 Theory and data

The ABMs surveyed have different roots for their decision logic: most prominent is the theory of planned behaviour, which prescribes that the behaviour of an individual is determined by the intention and perceived behavioural control of this individual. The intention in turn is influenced by the attitude and subjective norm of the individual. Some models are inspired by network or social network theory and the diffusion of innovations.

For energy efficiency, a variety of studies use utility functions to structure the decision-making logic of agents. The decision of households to adopt a technology is modelled by the agent calculating the decision with the maximum expected utility. This approach provides a systematic and potentially valid means of collecting data and allows multiple aspects of the adoption decision to be expressed as utilities. However, it is also limited by what data one can actually obtain, and by other general limitations such as the choice experiments that are the basis for the utility functions used (Hodgson, 2012).

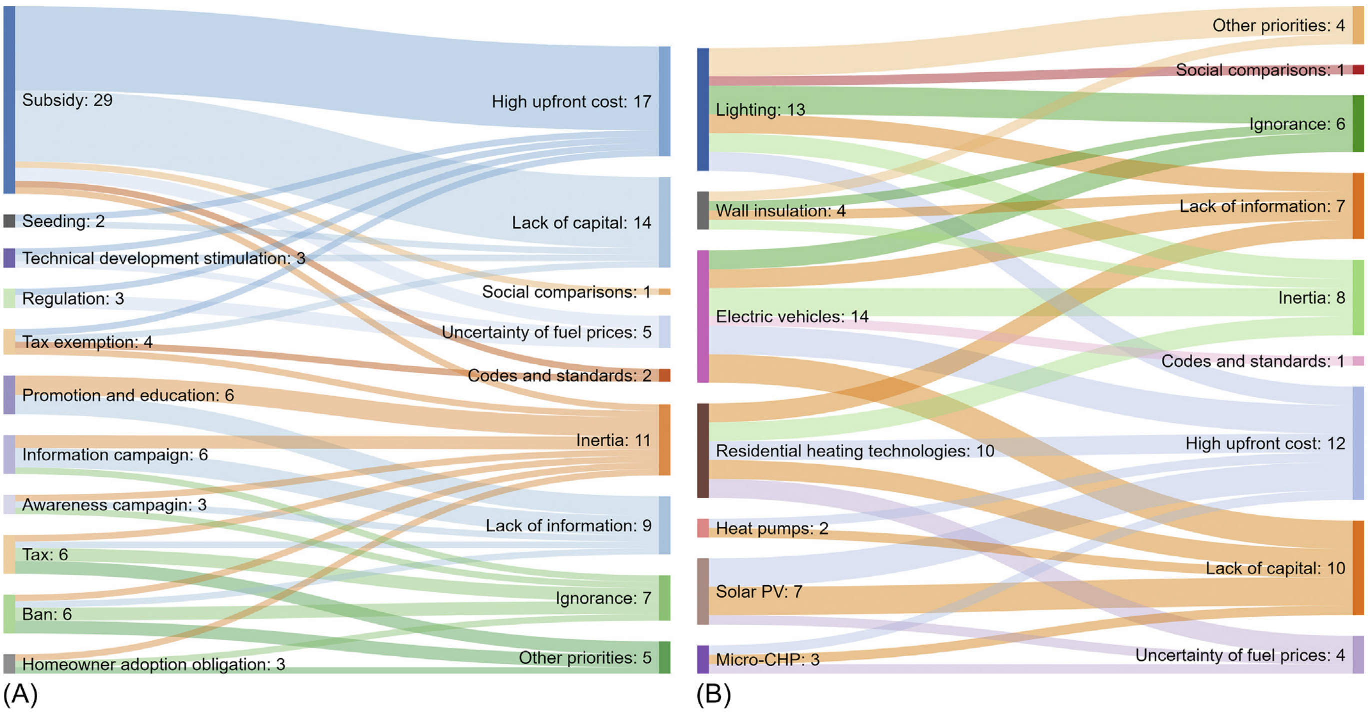

FIG. 4

Connections between policies, technologies, and barriers visualised in Sankey diagrams. (A) Links between policies and barriers. (B) Links between technologies and barriers.

From Hesselink, L., Chappin, E.J.L., 2019. Adoption of energy efficient technologies by households—barriers, policies and agent-based modelling studies. Renew. Sustain. Energy Rev. 99, 29–41.

Empirical data in agent-based models are normally used to provide for specifics on properties of barriers, technologies, households, and policies. It can also be used to structure the decision-making logic of agents: models that do so appear highly specific to a technology, barriers, and a population of households and lead to explicit policy-relevant findings.

4.1.4 Findings

Despite the fact that many types of policies are possible, there still is a focus on economic and financial instruments, such as subsidies or tax exemptions. These focus on barriers that relate to financing: high upfront costs and a lack of capital. There is not a consistent conclusion across the studies surveyed, mostly because policy conclusions differ for appliance types.

Key findings are that subsidies help to stimulate the adoption of EVs and alternative heating technologies, that banning incandescent lamps is the most effective policy to increase the adoption of efficient lighting, that an obligation for new homeowners to insulate their houses effectively helps to increase the adoption of wall insulation. Further, Hesselink and Chappin (2019) find that informational instruments are not as effective as other policies to stimulate EV adoption unless combined with a subsidy scheme.

The existing ABMs are specific to one or a few of the appliance types. This makes sense as the behaviour that end users have in relation to appliances may be very different, in terms of how they are purchased and how they are used. This implies that, for now, the field studies energy efficiency on the basis of cases, one by one, for a set of appliances, a set of barriers, and a set of policies.

ABM could also simulate other actors more explicitly, for example, the role of shops and other intermediary parties in the interconnected STS and a more elaborate institutional setting. This enables one to study more complicated policies, such as tradable 'white certificates' and energy efficiency tenders.

4.2 Consumer adoption of hybrid EVs

Our second case study simulates the market penetration of plug-in hybrid EVs (Eppstein et al., 2011). Eppstein et al.'s (2011) work was one of the first uses of agent-based modelling for studying in detail end-user adoption of such EVs, which combine a petrol engine with an electric engine. The petrol engine is refuelled at traditional petrol stations, while the electric engine is recharged at EV charging stations.

The context of Eppstein et al.'s (2011) study is the US end-user market, which, at the time of the study, showed low awareness of hybrid EVs, and which for many end users required relatively long-distance travel, beyond the range of pure EV technology at the time. Barriers hindering the uptake of EVs include reluctance to adopt unfamiliar technologies, uncertainty about battery life, recharging time and replacement costs, and difficulty in predicting cost of ownership (especially bearing in mind uncertainty about petrol prices). Studies of the US end users indicated that nonfinancial reasons were dominated in the decision to purchase a hybrid EV: for example, concern about CO_2 emissions. Altogether these comprise the energy behaviour dimensions studied by the paper.

The aims of Eppstein et al. (2011) are three:

> *present a framework for a novel agent-based vehicle consumer choice model, illustrate how such a model could be used by policy-makers and vehicle manufacturers to help prioritize investments influencing (hybrid EV) adoption, and identify additional empirical evidence that will be necessary to improve the predictive power of such a model.*

Thus, the case study explicitly identifies the purpose and limitations of the model, and treats the issues of data and policy implications. The model is simplified "due in large part to low model sensitivity to specific details or a lack of empirical data that could justify a more complex model."

Agents model end users, with attributes such as demographics (age, income, residential location), propensity to rationality, openness to EV adoption, years of car ownership, annual distance travelled by car, and attributes of their current car including traditional, hybrid, or pure EV. Each agent has a spatial neighbourhood which defines their geographical locality, and a social neighbourhood which corresponds to their nongeographical locality.

The decision-making procedure for end-user agents is a simple rule-based flowchart. Each year, the agent decides whether or not to buy a (new) car. If the agent decides to buy a car, it weighs up the relative costs and benefits of the available vehicles, and buys the most 'desirable' vehicle within its range of financial affordability.

The paper pays a lot of attention to calibrating the model based on the US data. Various sources are used. Attention is given to a heuristic parameter for each agent, which models her attitude to the desirability of reducing petrol consumption. This parameter is influenced by media coverage (of EVs) and the agent's susceptibility to media influence, and by decisions of agents in her spatial and social networks regarding EVs and the agent's susceptibility to social influence. The latter networks thus express geographic and socioeconomic homophily as depicted in Fig. 5.

Based on the simulation results, the paper identifies six possible levers relevant for policy around petrol and electrical vehicles, noting the interplay of policies at local, regional/state, and national levels:

- purchase price of EV;
- battery range of EV;
- petrol price relative to electricity price;
- ability of end users to accurately assess fuel costs for vehicle types;
- comfort level of vehicle end users in adopting new (EV) technology; and
- relative weight that end users place on rational-financial versus other reasons to save petrol.

Concluding, Eppstein et al. (2011) suggest that data are lacking on the proportion of end users that are comfortable enough with EV technology to be willing to

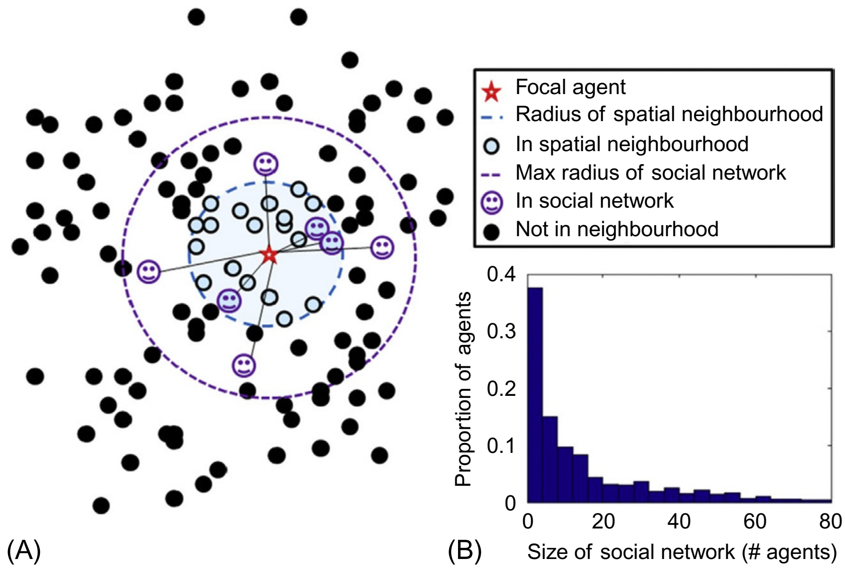

FIG. 5

(A) Agents' spatial and social neighbourhoods. (B) Long-tailed distribution of agents' social network sizes.

From Eppstein, M.J., Grover, D.A., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39, 3789–3802.

consider adopting early (Leigh and Yorke-Smith, 2011). Follow-on ABM and non-ABM studies reflect upon the model and results of the paper.

4.3 Energy management in smart grids

Our third case study explores scenarios around more end users becoming local producers of energy, such as through roof-top PV. Klaimi et al. (2017) study the integration of such *prosumers* into the electricity grid. Their interest is to maximise savings for end users, while retaining power supply balance, and allowing energy storage devices. Further, the authors aim to accommodate end users' preferences. We discuss the paper as a case study of a typical agent-based approach to electricity pricing and coordination in a smart grid, with focus on the end user.

Klaimi et al. (2017) consider four classes of agents, power generation companies, storage devices, prosumers, and traditional end users, and for each present an algorithm for the agent's behaviour. The agents negotiate in a cooperative, distributed manner in order to agree local electricity prices and distribution.

Klaimi et al. (2017) do not distinguish between the traditional power generation company and the distributor of electricity, often called the distribution system operator (DSO). In deregulated jurisdictions, such as most of Europe, these entities are separated. The focus of the paper is rather on agent-based modelling including energy storage devices. These devices can be used in nodes of the smart grid to store energy when supply exceeds demand and dispatches it when needed. Such a device can be a battery or even an EV. Optimal use of energy storage devices improves energy efficiency, acts as an arbitrage instrument, and maintains the storage device life.

The proposed approach is named ANEMAS (Agent-based eNErgy MAnagement in Smart grids). The aim is "resolve the generation intermittency [sic] problem and to optimize in real time the end-user bill by integrating a storage system and using multiagent algorithms (including negotiation)."

In addition to the distributed agents, the approach assumes a centralised system operator (implicitly, a DSO). The roles of the four agent classes are:

- Grid agent: satisfies the energy lack (by producing nonrenewable energy, or purchasing renewable or stored energy) and buys the excess of energy produced.
- Storage agent: controls the energy storage ('batteries').
- Production agent (including prosumer): controls the distribution of the energy which he produces.
- Consumption agent: negotiates the energy purchase with other end users and prosumers.

These decisions of the respective agents—energy purchase, storage, and distribution decisions—constitute the energy behaviour dimensions studied by the paper.

The approach follows a two-step protocol. In the first step, the 'proactive layer', the system operator predicts energy consumption and production for the next 24-hour period. In the second step, the 'reactive layer', the storage, production, and consumption agents plan and negotiate consumption for the next 1-hour period. Agents communicate by sending messages.

Consumption agents model the consumption of a household in a smart homes. Consumption is prioritised: the highest-priority demand in each 1-hour period must be met; the medium-priority demand can be delayed for a small time; the lowest-priority demand can be delayed for a longer time.

Production agents model sources of renewable energy production. Production agents may also be end users (i.e., prosumers); if so, the agent firsts aims to satisfy its own demand, and sells any excess energy. If a pure producer, the agent sells all its production: either directly to end users or to a storage agent.

Various synthetic scenarios are considered, although with predicted values of consumption and production taken from the French electricity network. The largest scenario has 30 production agents, 30 consumption agents, 1 storage agent, and 1 grid agent. Simulation results indicate that ANEMAS increases the use of renewable energy, reduces grid use beyond the local smart grid node, and reduces prices for end users.

Open questions about the paper are the origin and rationale for the algorithms proposed for each class of agent; the source and calibration of the utility functions of the consumption and production agents, and the extent to which they model end-user preferences; the negotiation protocols; multiple storage agents; and competition as well as cooperation. The last point leads to the topic of mechanism design in smart grids (Espana et al., 2018).

5 Directions

This chapter surveyed the opportunities and challenges in agent-based models for the social dynamics of energy end use. A pivotal question in the energy domain is what policies, institutions, markets, and market conditions we need in order to meet policy objectives in the context of the energy transition. ABMs fit well with studying all these user-related processes, as they can explicitly be studied under what conditions we may reach our policy targets. Thus, ABMs are found effective in informing policy making and in identifying possible energy transition pathways by exploring what-if scenarios. We considered in detail three case studies, which address domestic heating, EV adoption, and energy management in smart grids.

ABMs relate to many other chapters of this book. Chapter 4.1 looks at context of energy behaviour change while Chapter 1.1 discusses the psychological factors around energy conservation. Regarding building occupancy models, Chapter 3.2 notes the representation of complex effects and interactions at various scales—which suggests ABMs. Indeed, cross-fertilisation of ABM with the social sciences can enrich how energy behaviours are modelled.

The flexibility and utility of agent-based modelling leads to several directions for future research. First, multimodelling (Camus et al., 2015). Strachan et al. (2016) argue for dialogue between multiple models specifically to narrow the science-policy interface gap in the energy domain.

The second direction is serious games of energy use. These kinds of games expose stakeholders to the roles and positions of other stakeholders in the STS. Example of successful agent-based computer-supported serious games includes Bourazeri and Pitt (2014) and Kurahashi and Jager (2017).

Third, model reuse. It is still the norm in agent-based modelling that each problem studied is model afresh from the ground up; there is limited reuse of previous model parts. The literature analyses a number of barriers to model reuse (Rouchier et al., 2008).

The fourth direction is using large volumes of data and machine learning techniques. We have seen the use of data in agent-based modelling for the energy domain (Section 3.6). Advances in data availability and data science tools generate new opportunities and, perhaps, necessity, in data-driven ABMs. The literature reflects a debate on this point (Cao et al., 2015; Nye, 2013).

Fifth, ABM for urban planning. We noted in this chapter the interconnectedness of modern society and the centrality of energy. If ‘energy is everything’, then the utility of ABM for exploring energy use and behaviour suggests utility for urban planning (Perez et al., 2016), and successful examples already exist (Ghavami et al., 2016).

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