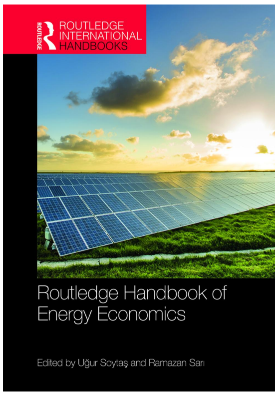

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Paths and processes in complex electricity markets

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Paths and processes in complex electricity markets

The agent-based perspective

Alessandro Sciullo, Elena Vallino, Martina Iori, and Magda Fontana

1 Electricity systems as complex systems

1.1 The complexification of electricity systems

An electricity market emerges from the interaction of several heterogeneous actors. On the one hand, generators, transmission system operators, distribution system operators, and retailers are engaged in producing and delivering a good with distinctive features: electricity is not storable, demand is subject to stochastic and temporal variations, and provision takes place via a physical network in which supply needs always to be equal to demand (Bollinger et al. 2016). On the other hand, households by virtues of policies aiming at discarding the traditional natural monopoly structure and at favoring generalized access and efficient economic conditions have assumed an unprecedented active role. Households can switch retailers and tariffs acting as a driver for competition and, by becoming prosumers, can participate in energy production and distribution. This interplay blurs the boundaries of the economic categories of demand and supply and casts doubts on the explanatory and predictive power of market models based on equilibrium.

The understanding of the electricity market behaviors requires the joint investigation of different processes like technology diffusion (i.e. smart grid), service innovation and the widening set of motivations for individual behaviors. Objectives like profit and utility maximization need to be complemented as the awareness of the consequences of climate change and the need for sustainable energy production and consumption increases.

This chapter aims to set out the ways in which complex systems thinking and modeling could be useful in understanding the functioning and evolution of the electricity markets. The final objective is to provide useful insights in order to address current and future policy challenges that is "to design appropriate economic and control mechanisms to handle demand and supply transactions among the increasingly heterogeneous and dispersed collection of participants in modern electric power systems" (Tesfatsion 2018).

1.2 Complex systems: a general outline

The study of social phenomena as complex systems has become a fruitful area of research and application over the last 30 years, particularly since the founding of the Santa Fe Institute in 1984. However, the application of the concepts developed in the complexity domain to the understanding of energy systems is relatively recent (Tesfatsion 2018; Vasiljevka et al. 2017; Bale et al. 2015; Moglia et al. 2018).

In biological and physical sciences and in engineering systems theory is widely used, exploiting the powerful representation of a system as a collection of its parts which are interacting among themselves. The branch of systems dynamics acknowledges the role of positive and negative feedback, that produces systems running out of control, and the role of virtuous and vicious cycles, in which systems can be kept on the same track for a long time. Starting from this background, scholars of the Santa Fe Institute investigated the common features of a range of systems exhibiting complexity, such as emergence, non-linearity, self-organization, co-evolution, adaptation (Holland 1995). Complexity studies analyze how processes which are different in nature and domain, such as physical, social and political phenomena, interact with each other, and, most importantly, influence each other, leading to the development of emergent properties at the system level (Fontana 2010, De Marchi and Page 2014).The core aim of this research stream is of course linked to the possibility to improve the management of complex systems thanks to the understanding of these features and principles.

Complexity science is presently an established domain of research, characterized by multidisciplinarity, including an increasing body of scholars in different disciplines (Squazzoni 2010), such as economics (Farmer and Foley 2009; Arthur 1999; Foxon et al. 2013; Fontana 2010), innovation (Bonifati 2010), and private and public management (Secchi and Neumann 2016; Anderson 1999; Teisman and Klijn 2008). The advocacy for the application of a broader range of complexity tools and approaches to economic issues is constantly increasing. Figure 36.1

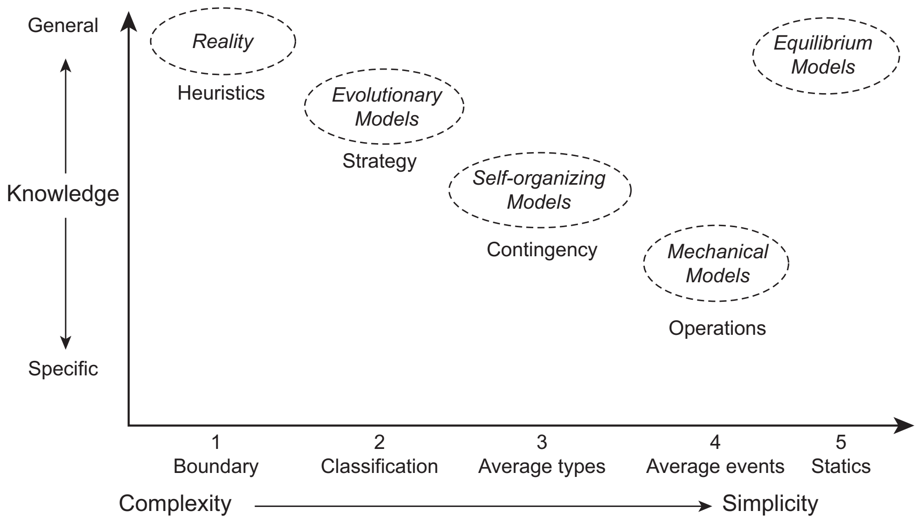

Figure. 36.1 Complexity versus simplicity (adapted from Bale et al. 2015)

illustrates the relation of modeling techniques in the field of complexity studies with the more conventional and simplistic ones, such as the calculation of an equilibrium given by the interplay between supply and demand. In the following paragraphs we focus on the features of energy systems that qualify these structures as suitable for a complexity oriented analysis.

1.3 Characteristics of complexity science and relevance for energy systems

One area where complexity methods can add value over other modeling methods is in addressing questions at the technology-policy-behavior interface by incorporating social and institutional elements in the study of energy systems.

Electricity is a peculiar commodity, in fact it is a homogeneous good produced by heterogeneous sources with different costs of production (Domanico 2007). It cannot be stored in large quantity, and it demands a continuous balance between demand and supply. For this reason a comprehensive simulation of electricity market should consider all the aspects and actors in the system and their interaction. Each of these entities cannot be imagined as independent and cannot be imagined as ordinary boundary condition (Chassin et al. 2014).

Energy systems thus can be understood as complex adaptive systems in that they are composed by interrelated, heterogeneous elements (agents and objects). In addition, there is no autonomous control over the whole system, and, in that sense, self-organized emergent behavior arises and it cannot be predicted by understanding each of the component elements separately. For example, the introduction of a new technology (an object) will influence the behavior of one or more individuals (agents), which leads to direct and indirect effects (such as resilience, security) on other parts of the system.

Energy systems exhibit both complex social and technological dynamics. Existing modeling approaches focus only on some of the aspects of this complexity (Bale et al. 2015). From a complexity perspective, energy systems are composed by (1) agents that interact through networks under the rules given by institutions, which leads to the development of emergent properties and co-evolutionary dynamics, (2) objects, such as technologies and infrastructures whose adoption is dynamic and fluctuating, and (3) the environment, which provides both the resources and also the social and political framework in which the dynamics of the energy system occur (Ibid.).

The crucial agents in energy systems are households and enterprises as energy consumers, energy conversion and supply companies, economic and environmental regulators, and local and central governments. These agents adapt and react to other agents' actions and to objects, and are heterogeneous in features, objectives and processes of decision-making. They interact through physical and social networks, by sharing information or learning from one another, influenced by social norms and institutional rules (Tesfatsion 2018; Vasiljevka et al. 2017). In this sense they do not own the perfect rationality that characterizes the entities of standard economic models (De Marchi and Page 2014). This may lead to self-organization and emergent properties, such as shared practices for energy use or given institutional arrangements for markets governing energy supply (Moglia et al. 2018). These interactions are dynamics over time and change following the availability of new objects and policies. However, as both technologies and institutions are embedded in positive feedbacks in the adoption process, change is subject to path dependency and systems experience lock-in phenomena (Unruh 2000). This implies that potentially advantageous innovations may not be adopted if they are not compatible with the current system, or if virtuous circles are not triggered (Bale et al. 2015).

Due to the heterogeneity of objects, agents, interactions and processes involved in energy systems, the application of complexity science in this domain calls for a methodology that should be able to promote a deep collaboration across disciplines, embracing the perspectives of mathematics, engineering, economics and the social sciences, as well as engagement with practitioners in the field.

2 Concepts and tools for dealing with complexity: agent-based modeling (ABM)

2.1 ABM, the right modeling for social sciences

Dynamics and properties of energy systems are thus inherently complex. As well as other social processes, they 'emerge' in an unpredictable way from many non – linear interactions among many heterogeneous elementary agents and they are not decomposable into separate sub-processes – economic, demographic, cultural – whose isolated analysis can be aggregated to give adequate analysis of the social process as a whole (Epstein and Axtell 1996; Gilbert 2004).

The challenge for social scientists is to find a way to deal with three main properties that characterize complex social systems (CSS): *heterogeneity* of agents and interactions; *emergence* as a non-linear process that link different levels of the system; *path-dependency* as the influence that the initial conditions may have on the dynamics of the system. In consideration of these complex properties it has been said that social science is often the actual hard science.[1]

As mentioned in paragraph 1, in order to explore this complexity, a modeling approach is needed to replace "the part of the universe under consideration by a model of similar but simpler structure [as] no substantial part of the universe is so simple that it can be grasped and controlled without abstraction" (Rosenblueth and Wiener 1945).

The best candidate to implement this modeling approach in social science is Agent Based Modeling. Through statistical models in fact it is not feasible to grasp heterogeneity and non-linearity. Other simulation techniques (Table 36.1), based on parameterized systems of differential equations are not able to capture physical, institutional and behavioral aspects and to combine empirical accuracy and analytical tractability (Borrill and Tesfatsion 2011). Some computational and computer-based simulations are efficient in grasping some emergent processes and dynamics aspects but are only partially suitable to represent and analyze heterogeneity and interaction. ABM is the only approach that allows representing many heterogeneous agents acting and interacting in an evolving multi-level environment following evolutionary rules of behaviors based on their learning processes.

Table 36.1 Social science simulation techniques (adapted from Gilbert and Troitzsch 2005)

Simulation technique		*No. of Levels*	*Interaction among agents*	*Complexity of agents*	*Number agents*
System dynamics		1	No	Low	1
Microsimulation		2	No	High	Many
Queuing models		1	No	Low	Many
Multilevel simulation		2+	Maybe	Low	Many
Cellular automata		2	Yes	Low	Many
ABM	Multi-agents	2+	Yes	High	Few
	Learning models	2+	Maybe	High	Many

ABM is a relatively young methodology that has been going through a fast development over the last two decades. In ABM social systems are modeled following a bottom-up approach as collections of autonomous interacting agents that operate within a computational world and adapt their behavior through learning procedures. Non-trivial properties at the macro-global level may arise from adaptation, learning and interaction mechanisms at the micro-individual level (Epstein 1999). In comparison to traditional equation-based modeling, ABM permits a more realistic representation of real-world systems composed of interacting distributed entities with limited information, limited possible responses, limited material resources and limited computational capabilities. The modeled systems are implicitly evolutionary as agents, like real people, can only acquire new data about their world locally and constructively, through interactions, and can have incomputable beliefs about their world that drive their behaviors and interactions (Borrill and Tesfatsion 2011).

Roughly speaking, an agent-based model is composed of three main ingredients (Epstein and Axtell 1996): *agents*, which are the people of artificial societies; *environment*, which is the natural or artificial landscape over which agents act and interact; *rules*, which define behaviors and interactions of agents and environment. Agents and environment should be clearly distinguishable in terms of *agency*, intended as the capability to autonomously act that is definitely what defines an agent (Gilbert and Troitzsch 2005).

Some principles should be considered in modeling ABM (Tesfatsion 2018):

1 *Agent scope*, that is, what agents represent (social, biological and/or physical entities).
2 *Agent definition and autonomy*. Agents are entities capable of acting over time on the basis of their own state (properties and rules) and their interactions are driven by rules embodied within agent states and not determined by the exterior.
3 *Constructivity* (*local and system*) that at any given time determines the action of an agent as a function of the agent's own state and the state of the modeled system as the ensemble of agent states.
4 *Historicity* or *path-dependency* that strongly connects all subsequent events in the modeled system to the given initial agent states.

In this framework, the modeler is an observer with a role that is limited to the initial settings and to the non-perturbational observation and analysis.

ABM definitely offer to social scientists a virtual laboratory where experiments can be carried out to develop and explore theories and dynamic aspects of change and to observe relations between different levels of the social systems (Gilbert and Troitzsch 2005).

2.2 How to design and implement an ABM in practice: toward a standardization

In order to build an ABM two main requirements have to be satisfied: a good conceptual design and formalization and a proper performing software implementation. One of the main criticalities for ABMs exploitation has been the lack of standardization with regard to both these aspects, a condition that hampered the starting of a cumulative knowledge process and the establishment of a robust community of scientists in the field. In the last decade two promising tools for ABM standardization have been gaining relevance: Netlogo as the programming language and the ODD protocol as a standardized conceptual framework.

Modeling cycle and ODD protocol

Autonomous processes that derive from agents' behaviors and decisions could make ABMs unpredictable. ABM modeling activity should be intended as a circular process that drives continuous

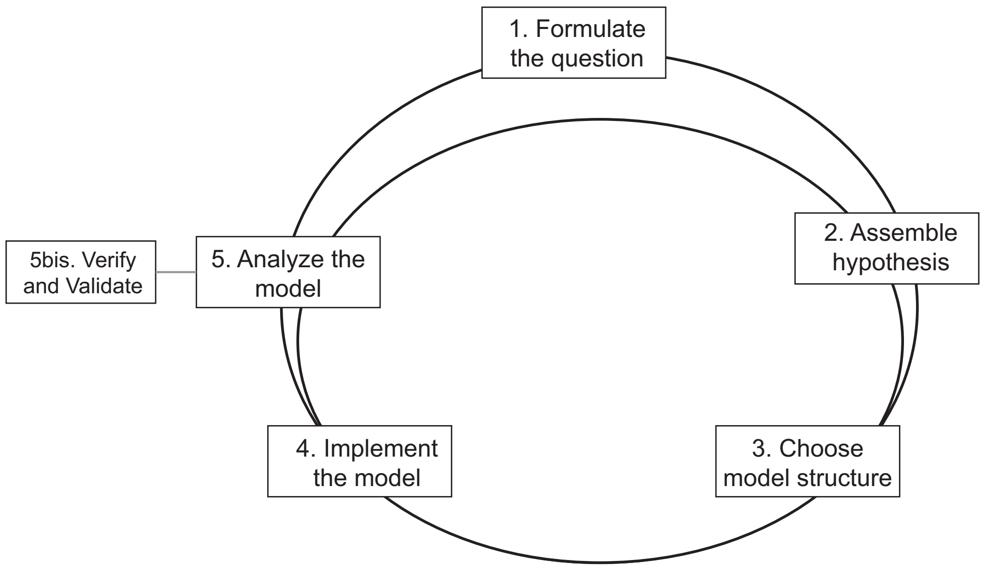

Figure 36.2 The modeling cycle (adapted from Railsback and Grimm 2012)

refinements and growing complexity of the model on the basis of the results produced by the model itself, as it is shown in Figure 36.2.[2]

1 *Formulate the question*. It is the primary filter for designing a model even if the question itself can be reformulated and refined along the modeling activity.
2 *Assemble hypotheses for essential processes and structures* that are explanatory hypotheses about the main components of the system under observation and their behaviors and interactions. They have to be simple in order to develop a first understanding of the system behavior and then they should be gradually specified and detailed so that model grows in complexity at each cycle.
3 *Choose scales, entities, state variables, procedures and parameters*, that is the (written) formulation of the model aimed at mathematically formalizing and operationalizing the hypotheses.
4 *Implement the model* through coding. Although it may seem a mere technical part of the cycle it is relevant to explore, in the logical way provided by programming languages, the rigor and consequences of hypotheses and assumptions.
5 *Analyze, test, and revise the model*. This is the actual scientific task aimed at assessing the robustness of the hypotheses and of the model itself. The *validation* activity (5bis in the figure) deserves particular attention as it is aimed at verifying, beyond the logic of the model, if the simulated outcomes reproduce, at least in stylized forms, the distribution of the phenomena in the real world that the model has been designed to describe.

Standardizing ABMs' designing process is crucial in order to force modelers in clearly formulating and formalizing their hypothesis and to make it possible to re-implement the models and, to the extent it is feasible, replicate their results.[3]

To bring the benefits of standardization to ABMs, a large group of experienced modelers developed the *Overview, Design concepts, and Details Protocol (ODD)* (Grimm et al. 2010).

The protocol is structured in three sections:

- *Overview*, aimed at providing a general description of what the model is about and how it is designed. The overview is divided in three subsections: purpose (i.e. scope and objective); entities, state variables and scales (i.e. agents, environment and properties); and process overview and scheduling (i.e. dynamics of the simulated system).
- *Design concepts*, aimed at depicting the model's essential components that characterize in details agents, environment and rules in order to deal with heterogeneity, emergence and path-dependency. It is divided into ten subsections: basic principles, emergence, adaptation, objectives, learning prediction, sensing, interaction, stochasticity, collectives, and observation.
- *Details*, which provide all the information needed to make the model implementation clear and repeatable. It is divided in three sections: initialization (i.e. initial conditions of simulation), input data (i.e. how the model is fed), and submodels (i.e. modeling of sub-systems and processes).

Object-oriented programming and Netlogo

After having defined it conceptually, making an ABM a working simulation is above all a matter of computation and for this reason ABM has been developing in the last two decades jointly with the development of IT sciences. Among the different programming languages, object-oriented programming (OOP) is the most suitable as the main element of an OOP are objects, virtual structures that hold both data (variables) and procedures (algorithms). Agents and environment are thus naturally implemented in OOP as objects. The agent's internal states (stable and variable properties) are implemented as the object data while the agent's behaviors are implemented as objects' procedures.

A recent review listed approximately 80 specific software tools for building ABMs that differentiate in their suitability to different fields of application, in their performance in terms of computational power and in the required programming skills (Abar et al. 2017).

Among these platforms, Netlogo[4] has been growing in diffusion among modelers for the last decade and today is considered as the standard for building ABMs of social phenomena.

Netlogo is developed in Java and it has been designed as an exploitation of the Logo language (a language created to teach programming to young students). It is a semi-natural programming language perfectly suitable to develop ABM as its main programming elements are agents ("turtles", patches and links) and it provides a huge library of primitives (both variables and methods) to model their properties, interactions and behaviors. These ABM-friendly features stand behind the worldwide success of Netlogo in modeling community even if it is not the most performing software tool. In fact, while on the one hand Netlogo makes it possible to "play" with models also for researchers without any (or very few) skills in programming, on the other hand, even in the case of experts programmers dealing with the designing of models that require large amount of computational power, Netlogo still provides a powerful environment to assess at a small scale the overall functioning of the model.

3 Energy-complexity models: some examples

3.1 Two generations of models

Looking at the electricity systems as paradigmatic example of socio-technical systems (Bollinger et al. 2016), here some agent-based simulations are proposed as examples of their potential in investigating electricity systems. By representing the behavior of real actors of the systems (whose importance is highlighted in Chapter 17), ABMs allow us to observe how the technical and social subsystems of an infrastructure co-evolve, and which overall system behavior might emerge from their ongoing interactions, at multiple system levels and time scales

It is clear that the worldwide process of liberalization and the recent technological advances have shaped the evolution of ABM in electricity markets. The introduction in the market of new autonomous actors and the transition from a monopolistic centralized structure to a system in which heterogeneous distributed agents strategically act favors the use of ABM as a crucial tool in electricity market simulation. In the electricity market context, agents' behavior should respect some real, physical and economic, constraints. Moreover, these entities have an imperfect local information about the environment and the purposes of other agents. They aim at satisfying some own specific goals, adapting their behaviors during the simulation and making decisions in a very uncertain environment, with few information about future events. The ABM paradigm can reproduce all these key features of the electricity market in several conditions, considering also out-of-equilibrium situations or states in which multiple equilibria are present.

In the following a brief literature review of ABM application in the field of electricity systems is presented.[5] In the early 2000s, shortly after the beginning of the deregulation process, the first agent-based studies (among which Bower and Bunn 2000) started appearing, focusing on the challenges that decentralized open markets were facing. At the beginning they mainly dealt with the design of wholesale markets, the price forecasting and the bidding strategies (Guerci and Rastegar 2009). Furthermore, some large-scale simulations have been designed to catch all these aspects of the market (Praça et al. 2003; Conzelmann et al. 2005; Grozev et al. 2005; Sun and Tesfatsion 2007). This part of literature is constantly updated and, during the years, models have been improved with the introduction of network constraints (Veit et al. 2009) and statistical validation (Young et al. 2014). It is important to emphasise that in these early simulations the main agents are generator companies, whereas demand is mainly considered as completely inelastic and consumers do not have an active role in the market.

One may think that a new stream of ABM literature about electricity market arose with the growing use of renewable sources in the process of energy generation, occurred during the first decade of 2000s. Several simulations, adding this new element of investigation, tried to respond to some rising concerns about reliability of supply, network balancing and prediction of wholesale prices (Sensfuss et al. 2008; Cai et al. 2011; Bublitz et al. 2014). As in the previous analyses, the main entities described in these simulations are production companies.

Finally, analysing the literature is evident that the advancement of technology in the last few years and the institutional interest on smart grids moved the scholars' attention toward the implementation of ABM simulations able to describe the future restructured electricity market. These investigations are connected to the previous branch of literature, since the future electricity market will make the demand side more flexible, leading to a successful integration of renewable sources. However, they represent an additional challenge in this already complex system. Smart technologies brought out new participants in the market: consumers will have an active role and retailers will become essential actors in the future electricity market. It may be supposed that these considerations lead to the introduction of retailers (Yousefi et al. 2011) and consumers (Thimmapuram and Kim 2013; Kowalska-Pyzalska et al. 2014) as dynamic agents in the new simulations. In the literature, the main branches of investigation about smart grids concern its effects on the wholesale market (Lupo and Kiprakis 2015; Pinto et al. 2015), the analysis of future scenarios in which there are high penetration of smart appliances and of distributed generators (Kahrobaee et al. 2014), and some largescale simulations able to describe several aspects both of retail and wholesale markets (Aliprantis et al. 2010; Rylatt et al. 2013). Despite that, the number of studies about retail market is still restricted and mainly concentrated on the supply side or the demand one, instead of considering both these parts of the market (a first attempt is represented by Bompard et al. 2007). However, supply and demand are deeply interconnected, influencing each other, and both are fundamental aspects in the implementation of a well-functioning retail market.

3.2 Three energy-complexity models in details

In this section we report some examples of researches in this domain that have been performed in the UK.

In the Future Energy Decision Making for Cities project a dynamical network model has been developed to analyse the influence of social networks on the adoption of domestic energy technologies. Unexpected system-level behaviors emerge by the interaction of households within the network. This work has the advantage to integrate social aspects with technological and economic dimensions in a quantitative model which can be useful for the assessment of local authority interventions (Bale et al. 2014).

The Complex Adaptive Systems, Cognitive Agents and Distributed Energy (CASCADE) project developed an agent-based model on energy infrastructure (Rylatt et al. 2013). The aim is to gain policy- and industry-relevant insights into the smart grid concept. It includes heterogeneity of behaviors among different social, economic and technical actors, and agents learning capacity. Three models are integrated: electricity supply and demand, the electricity market and power flow. Weather data is used to inform the variation of the renewable energy generation: this allows to deal with the issue of intermittency, which is crucial for grid balancing and for the profitability of energy suppliers. The CASCADE models have found that an aggregator can stabilize the demand across groups of domestic households together with smart energy control and communication devices. This result contrasts with alternative methods that use wholesale price signals, which produce instability. Furthermore, the project Preventing Wide-Area Blackouts Through Adaptive Islanding of Transmission Networks utilized graph theory to analyse how local behavior of elements of an electrical grid influences the resilience of the grid as a whole (Bialek 2012). Foxon (2011) analyses the transition to sustainable low carbon energy system, focusing in his framework on five key coevolving systems: technologies, institutions, business strategies, user practices and ecosystems. Bale et al. (2015) provide further examples of applications of complexity studies to energy systems, with some highlights on works that addresses environmental sustainability and long-term changes in the energy domain.

4 The relevance of ABM for energy systems: potential for policy design and the way forward

The nonlinearities that ground the functioning of complex systems make policy design and evaluation particularly difficult. Complex systems are not governed by the traditional causality: feedback mechanisms generated by adaptation to policy intervention and heterogeneity in agents and in their response require methods that go beyond the traditional statistical approaches.

Agent-based models meet the challenge of exploring complexity from a number of perspectives. Their ability of capturing the heterogeneity in behaviors and features of the actors and to explicitly model the interaction cuts down the most important modeling barriers faced by the traditional approaches. The possibility of including geo-localized data also ensures maximum precision in defining the relationship between the simulated scenarios and the relevant environment.

In addition, the output of the simulation embraces all the possible levels of analysis since micro, meso and macro layers can be investigated simultaneously in a temporal dimension. With respect to other approaches, the observed system can be explored in terms of structure and processes. That is to say, that the typical output of an agent-based model includes rates, levels, time series, and equilibrium values (if any).

Important limitations of agent-based models, such as the high number of parameters and the crucial role of stochasticity in determining the dynamics of the simulated system, have recently been overcome by the advances in the techniques of parametrization, calibration, and in robustness analyses.

These properties make agent-based simulation an ideal candidate to model the energy market. The interplay between the physical infrastructures, the market actors and the social environment can be easily modeled by coupling agent-based simulation with network analysis. At the same time the increasing richness of available data allows for correct parametrization and for a safe simulation of evolutionary scenarios (see in this sense Bale et al. 2015; Tesfatsion 2018). The awareness of the potentiality of agent-based model is spreading beyond the academic arena towards government and policy advisors as witnessed by the design of European simulation platforms for electricity systems that include technical, economic and social factor (Covrig et al. 2016).

However, there is room for improvements. ABMs have been used so far mainly to model Transmission/Distribution dynamics and their application should be extended to the analysis of consumer behavior (Vasiljevka et al. 2017). The liberalization of electricity markets and the drive towards renewables-based generation are inciting a shift towards a more bottom up structure of electricity systems. This means that electricity production is increasingly determined by the distributed decisions of numerous actors to invest in and deploy (distributed) generation technologies. The interactions of these actors with one another – in social networks, markets and organizations – will influence, and be influenced by, the physical infrastructure. Insofar as electricity networks act as essential mediators of and constraints on electricity supply and demand, understanding their technical functionality is essential to shape more sustainable, reliable and resilient electric power systems.

Acknowledgments

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Notes

1 Simon, H. (1987) *Giving the Soft Science a Hard Sell*, Boston Globe, May 3rd, Boston.
2 In Figure 36.2 the black line is the original proposed by the authors. We proposed the grey circle as the actual need of reformulating the questions is unlikely to emerge at each iteration of the cycle.
3 ABMs are not deterministic by definition. The results produced by the procedures implemented to simulate nonlinearity of the simulated processes are unlikely to be the same even when simulations start from the same initial conditions.
4 NetLogo is a multi-agent programmable modeling environment. It is authored by Uri Wilensky and developed at the CCL. It can be downloaded from Northwestern Netlogo.
5 A complete review of the literature falls beyond the scope of this paper. For a more detailed survey, see Ringler et al. (2016), Sensfuss et al. (2007), and Zhou et al. (2007).

References

Abar, S., Theodoropoulos, G.K., Lemarinier, P., O'Hare, G.M.P. (2017) Agent based modelling and simulation tools: A review of the state-of-art software. *Computer Science Review*, 24: 13–33.

Aliprantis, D., Penick, S., Tesfatsion, L., Zhao, H. (2010) Integrated retail and wholesale power system operation with smart-grid functionality. In: Power and Energy Society General Meeting.

Anderson, P. (1999) Perspective: Complexity theory and organization science. *Organization Science*, 10(3): 216–232.

Arthur, W.B. (1999) Complexity and the economy. *Science*, 284: 107–109.

Bale, C.S., McCullen, N.J., Foxon, T.J., Rucklidge, A.M., Gale, W.F. (2014) Modeling diffusion of energy innovations on a heterogeneous social network and approaches to integration of real-world data. *Complexity*, 19: 83–94.

Bale, C.S., Varga, L., Foxon, T.J. (2015) Energy and complexity: New ways forward. *Applied Energy*, 138: 150–159.

Bialek, J. (2012) Preventing wide-area blackouts through adaptive islanding of transmission networks. UKERC The Meeting Place.

Bollinger, L.A., van Blijswijkb, M.J., Dijkemac, G.P.J., Nikolicb, I. (2016) An energy systems modelling tool for the social simulation community, *Journal of Artificial Societies and Social Simulation*, 19(1): 1.

Bompard, E.F., Abrate, G., Napoli, R., Wan, B. (2007) Multiagent models for consumer choice and retailer strategies in the competitive electricity market. *International Journal of Emerging Electric Power Systems* 8(2).

Bonifati, G. (2010) 'More is different', exaptation and uncertainty: Three foundational concepts for a complexity theory of innovation. *Economics of Innovation and New Technology*, 19(8): 743–760.

Borrill, P.L., Tesfatsion, L. (2011) Agent-based modeling: The right mathematics for the social sciences? The Elgar companion to recent economic methodology, Edward Elgar Publishing.

Bower, J., Bunn, D. W. (2000) Model-based comparisons of pool and bilateral markets for electricity. *The Energy Journal*, 21(3).

Bublitz, A., Genoese, M., Fichtner, W. (2014) An agent-based model of the German electricity market with short-time uncertainty factors. In: 11th International Conference on the European Energy Market.

Cai, C., Jahangiri, P., Thomas, A. G., Zhao, H., Aliprantis, D. C., Tesfatsion, L. (2011) Agent-based simulation of distribution systems with high penetration of photovoltaic generation. In: IEEE Power and Energy Society General Meeting.

Chassin, D.P., Fuller, J.C., Djilali, N. (2014) An agent-based simulation framework for smart grids. *Journal of Applied Mathematics*, 2014: 12.

Conzelmann, G., Boyd, G., Koritarov, V., Veselka, T. (2005) Multi-agent power market simulation using EMCAS. In: IEEE Power Engineering Society General Meeting. 3.

Covrig, C., De Santi, G., Fulli, G., Masera, M., Olariaga, M. Bompard, E., Chicco, G., Estebsari, A., Huang, T., Pons, E., Profumo, F., Tenconi, A., De Doncker, R., Grigull, M., Monti, A., Stevic, M., Vogel, S. (2016) A European platform for distributed real time modelling & simulation of emerging electricity systems, Technical Report, Publications Office of the European Union, Bruxelles. DOI: 10.2790/24617

De Marchi, S., Page, S.E. (2014) Agent-based models. *Annual Review of Political Science*, 17: 1–20.

Domanico, F. (2007) Concentration in the European electricity industry: The internal market as solution? *Energy Policy*, 35(10): 5064–5076.

Epstein, J.M. (1999) Agent-based computational models and generative social science. *Complexity*, 4(5): 41–60.

Epstein, J.M., Axtell, R. (1996) Growing artificial societies. Social Science from the Bottom Up. Brookings Institution Press, Washington, DC.

Farmer, J.D., Foley, D. (2009) The economy needs agent-based modelling. *Nature*, 460: 685–686.

Fontana, M. (2010) Can neoclassical economics handle complexity? The fallacy of the oil spot dynamic. *Journal of Economic Behavior & Organization*, 76(3): 584–596.

Foxon, T.J. (2011) A coevolutionary framework for analysing a transition to a sustainable low carbon economy. *Ecological Economics*, 70: 2258–2267.

Foxon, T.J., Köhler, J., Michie, J., Oughton, C. (2013) Towards a new complexity economics for sustainability. *Cambridge Journal of Economics*, 37: 187–208.

Gilbert, N. (2004) Agent-based social simulation: Dealing with complexity. *The Complex Systems Network of Excellence*, 9(25), 1–14.

Gilbert, N., Troitzsch, K. (2005) *Simulation for the Social Scientist.* Oxford University Press, Oxford, UK.

Grimm, V., Berger, U., DeAngelis, D., Polhill, J.G., Giske, J. (2010) The ODD protocol: A review and a first update. *Ecological Modelling*, 221: 2760–2768.

Grozev, G., Thatcher, M., De Silva, P., Chan, W.Y. (2005) NEMSIM: Agent-based simulator for Australia's national electricity market. In: SimTecT 2005 Conference Proceedings.

Guerci, E., Rastegar, M.A. (2009) From uniform auction to discriminatory auction: Assessment of the restructuring proposal for the Italian electricity day-ahead market. EUI Working Paper RSCAS 2009/69, European University Institute, Robert Schuman Centre for Advanced Studies.

Holland, J.H. (1995) *Hidden Order: How Adaptation Builds Complexity*. Addison-Wesley, New York, NY.

Kahrobaee, S., Rajabzadeh, R.A., Soh, L.K., Asgarpoor, S. (2014) Multiagent study of smart grid customers with neighbourhood electricity trading. *Electric Power Systems Research*, 111.

Kowalska-Pyzalska, A., Maciejowska, K., Suszczynski, K., Sznajd-Weron, K., Weron, R. (2014) Turning green: Agent-based modelling of the adoption of dynamic electricity tariffs. *Energy Policy*, 72.

Lupo, S., Kiprakis, A. (2015) Agent-based models for electricity markets accounting for smart grid participation. In International Conference on Wireless and Satellite Systems (pp. 48–57). Springer, Cham.

Moglia, M., Podkalicka, A., McGregor, J. (2018) An agent-based model of residential energy efficiency adoption. *Journal of Artificial Societies and Social Simulation*, 21(3).

Pinto, T., et al. (2015) Smart grid and electricity market joint simulation using complementary multi-agent platforms. In: PowerTech.

Praça, I., Ramos, C., Vale, Z., Cordeiro, M. (2003) MASCEM: A multiagent system that simulates competitive electricity markets. *Intelligent Systems*, 18(6).

Railsback, S., Grimm, V. (2012) *Agent-Based and Individual-Based Modeling: A Practical Introduction*. Princeton University Press, Princeton, NJ, US.

Ringler, P., Keles, D., Fichtner, W. (2016) Agent-based modelling and simulation of smart electricity grids and markets: A literature review. *Renewable and Sustainable Energy Review*, 57.

Rosenblueth, A., Wiener, N. (1945) The role of models in science. *Philosophy of Science*, 12(4): 316–321.

Rylatt, M., et al. (2013) CASCADE: An agent based framework for modeling the dynamics of smart electricity systems. *Emergence: Complexity and Organization*, 15(2).

Secchi, D., Neumann, M. (2016) *Agent-Based Simulation of Organizational Behavior*. Springer, Cham.

Sensfuss, F., Ragwitz, M., Genoese, M. (2008) The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. *Energy Policy*, 36(8).

Sensfuss, F., Ragwitz, M., Genoese, M., Möst, D. (2007) Agent-based simulation of electricity markets: A literature review. *Working Paper Sustainability and Innovation S5/2007*. Fraunhofer ISI.

Squazzoni, F. (2010) The impact of agent-based models in the social sciences after 15 years of incursions. *History of Economic Ideas*, 197–233.

Sun, J., Tesfatsion, L. (2007) Dynamic testing of wholesale power market designs: An open-source agent-based framework. *Computational Economics*, 30(3).

Teisman, G. R., Klijn, E. H. (2008) Complexity theory and public management: An introduction. *Public Management Review*, 10(3): 287–297.

Tesfatsion, L. (2018) Electric power markets in transition: Agent-based modeling tools for transactive energy support. In Hommes, C., LeBaron, B. (eds.) *Handbook of Computational Economics*, volume 4. Elsevier, Amsterdam.

Thimmapuram, P.R., Kim, J. (2013) Consumers' price elasticity of demand modeling with economic effects on electricity markets using an agent-based model. *Transactions on Smart Grid*, 4(1).

Unruh, G.C. (2000) Understanding carbon lock-in. *Energy Policy*, 28(12), 817–830.

Vasiljevka J., Douwb, J., Mengolini, A., Nikolic, I. (2017) An agent-based model of electricity consumer: Smart metering policy implications in Europe download. *Journal of Artificial Societies and Social Simulation*, 20(1): 12.

Veit, D.J., Weidlich, A., Krat, J.A. (2009) An agent-based analysis of the German electricity market with transmission capacity constraints. *Energy Policy*, 37(10). 4132-4144.

Young, D., Poletti, S., Browne, O. (2014) Can agent-based models forecast spot prices in electricity markets? Evidence from the New Zealand electricity market. *Energy Economics*, (45).

Yousefi, S., Moghaddam, M.P., Majd, V.J. (2011) Optimal real time pricing in an agent-based retail market using a comprehensive demand response model. *Energy*, 36(9).

Zhou, Z., Chan, W.K.V., Chow, J.H. (2007) Agent-based simulation of electricity markets: A survey of tools. *Artificial Intelligence Review*, 28(4).