A review of agent-based models for forecasting the deployment of distributed generation in energy systems

Jason G. Veneman, M.A. Oey, L.J. Kortmann, F.M. Brazier, L.J. de Vries
Delft University of Technology
veneman (at) gmail (dot) com, {M.A.Oey, L.J.Kortmann, F.M.Brazier, L.J.deVries}@tudelft.nl

Keywords: distributed generation, energy forecasting, agent-based modeling, consumer behavior, product deployment

Abstract

Agent-based models are seeing increasing use in the study of distributed generation (DG) deployment. Researchers and decision makers involved in the implementation of DG have been lacking a concise overview of why they should consider using agent-based modeling (ABM) for forecasting purposes. Since this particular field of inquiry has only developed over the past few years there has yet to be a review of ABMs of DG deployment. In light of these developments the reasons to consider using ABM to develop a deeper understanding of the transition issues relevant to the increasing use of DG are presented. The current state of ABMs of DG deployment is reviewed followed by areas for improving these models and directions for further research.

1. INTRODUCTION

The development and implementation of new technologies in the electricity generation sector, specifically DG, are upending previous modes of operation for the actors involved in the functioning of and planning for energy infrastructures. In both developed and developing countries there is a drive to increase the share of alternative, smaller scale, energy generation systems like DG sources. However, implementing these technologies is not a simple plug and play operation and institutional and social issues must be accounted for as well. The deployment of DG systems such as rooftop solar photovoltaic (PV) and micro combined heat and power (CHP) systems are seeing increasing interest due to factors like increased demand for reliable sources of electricity, general electricity market uncertainty, energy security, constraints on new transmission line construction, climate change concerns and utility deregulation (Pepermans et al., 2005; Cossent et al., 2009; Lopes et al., 2007). In addition, regulations such as the EU Energy Policy and the Renewable Portfolio Standards will likely lead to further penetration of DG in electricity networks. Increased deployment of DG implies that there will be many more stakeholders affecting the evolution of an energy system since generation could move from a small number of large plants to a large number of small plants. The convergence of these factors has led to the creation of models for looking into transition pathways that take into account the complex socio-technical interactions that are driving these changes.

A report prepared for the European Commission (EC) declares that the current models being used by the EC are ill-suited to account for changes in the energy sector (e.g. carbon trading/taxes, deregulation) and calls for a broadening of the modeling framework beyond energy-environment-economy models to include network structure and agent behavior (Grohnheit, 1999). One tool that is used frequently in energy system forecasts are MARKAL (MARKet ALlocation) models. These models are used by the International Energy Agency (IEA) and many other agencies in international governments to help in the planning of their nation's energy system. Since the development of MARKAL models started in the late 1970s and they are used by so many organizations they are able to account for many of the factors that make up the real energy economy and are quite robust. However, despite their ability to account for many inputs that affect a given energy economy their outputs are based upon just minimizing a system's total discounted cost or total discounted surplus over a certain time period (Connolly et al., 2010). Since many other elements would seem to be important in helping to forecast the development of energy systems newer models are being developed to examine how resource use, CO_2 output, cost and other factors may change if an energy system develops with DG and the bottom-up interactions between the many DG consumers are taken into account. The issues with conventional models contrasted with the results from the growing body of research into agent-based models are showing some new approaches to help provide these answers.

2. TRADITIONAL APPROACHES TO MODELING DG

In order to realize the use of more sustainable energy generation, policy makers, planners and others involved in the development of energy infrastructures employ decision support mechanisms. Complex socio-technical systems like energy infrastructures evolve through the interactions of many stakeholders and the technological developments employed in the systems. The actors involved in these decisions behave strategically and often have diverging interests about how a system should evolve which makes it difficult to understand and explain how changes to a system might play out. To address this concern modeling "can be used to understand and convey to policy makers the dynamic behavior of complex systems" (Mayer, 2009, 848). Decision support models are not geared towards finding a system optimum but more towards allowing policy makers to explore possible futures of a system's development and what-if scenarios (Dam and Lukszo, 2010). Since the design of infrastructures is becoming ever more complex it is this explanatory and scenario exploratory feature of modeling that makes an interesting area for research.

The traditional approaches to modeling technological change in infrastructures include optimization and equilibrium models. While these models can produce optimal solutions their usefulness in trying to find realistic solutions to the issues facing energy infrastructures is limited due to the vast complexity of such systems. Optimizations do not adequately deal with and account for the incomplete information and emergent behavior that is inherent in large socio-technical systems like energy infrastructures. If there is to be a significant transition to modern, cleaner forms of energy production then great progress needs to be made in developing models that help scientists, policy makers and citizens understand what can be done to move faster towards a new energy infrastructure.

A range of models have been developed in the energy sector for forecasting and for looking into the integration of new technologies, including DG, in energy systems. Connolly et al. (2010) provides a review of over 30 different models that can be used to analyze the integration of renewable energy sources and only one of those models, EMCAS (Electricity Market Complex Adaptive System), is an agent-based model (ABM). Why there are so few ABMs being used for these types of models may be attributed to several factors including the relatively young age of ABM techniques, the unfamiliarity of modelers and decision makers with ABMs, and a disregard for some of the problems inherent with non-ABM techniques. The remainder of this section will expound upon the shortfalls of conventional (i.e. non-ABM) models while the following sections will provide an overview of ABM, its advantages, and where they are being used in the energy sector.

Research into the use of computer models as a possible policy making aid increased steadily through the 1950s and 1960s in line with the increasing use of computers for other business and government functions. Seeing the amount of time and money being put towards these models and the questionable usefulness of their output prompted Douglas Lee to write an article, "Requiem for Large-Scale Models" (Lee, 1973), calling for their discontinuation and detailing the flaws that he felt were inherent in computer modeling. Since that article was written computing, modeling theory, and modeling practice have further developed to the point where some of Lee's criticism are now moot - particularly those related to hungriness and mechanicalness (e.g. limited data handling capability of older computers and numerical error resulting from the few significant digits that older processors were capable of handling).

However, models today are still susceptible to Lee's other criticisms. In discussing the wrongheadedness of models Lee states that there is a "deviation between claimed model behavior and the equations or statements that actually govern model behavior" and that a model's structure is "adaptable to any kind of system performance that might be encountered" (Lee, 1973, p. 165). These statements point out a core deficiency of equilibrium and optimization based models which are built upon complicated equations that purport to capture system interactions and produce meaningful outputs. The constraints embedded within these equations are often developed for mathematical convenience rather than being attributable to any real world phenomena. The complicatedness of conventional models is found to be a problem because while the relationships between components of a large system may be known "their microscopic behavior is largely unknown" (Lee, 1973, p. 166). The assumption that these large relationships between model components hold true when the variables within a component "are allowed to vary independently has no basis in theory or experience" (Lee, 1973, p. 166). Even with today's computing power it would be impossible for an optimization or equilibrium model to find a solution to an equation with the very large number of variables necessary to adequately account for this issue. This issue is evidenced in a recent paper on energy system planning which laments that the "power of global optimization is compromised by the computational effort required to explore such large non-linear problems" (Beck et al., 2008, p. 2800).

MARKAL based models are widely used to forecast a region's energy system development but its outputs are only based upon minimizing a system's total discounted cost or total discounted surplus over a certain time period. When one is investigating an energy system with DG the large number of generators and market participants that must be modeled mean that far greater demands are placed on the model to accurately account for the interactions within a system. The biggest detriment to using a MARKAL model for looking into issues related to DG deployment is that they lack the resolution to model many smaller generators as opposed to the large generation units it was designed to account for. The fact that the model was written in GAMS (General Algebraic Modeling System) - which is not an object oriented programming language - would seem to preclude it from ever being handle the higher resolution that DG would require (Bruckner et al., 2005).

3. AGENT-BASED MODELING: ADVANTAGES AND DISADVANTAGES

Techniques related to complex systems theory are providing decision makers with insights into such problems. One area of complexity theory that is especially amenable to studying problems related to complex adaptive systems is agent-based modeling. ABM and its ability to represent complex systems and capture emergent behavior that is similar to what goes on in the real world is a very promising tool that could be useful in accelerating the transition. Instead of taking the optimization viewpoint and creating models that show "what should be" ABMs can show "what could be" under different scenarios (Ma and Nakamori, 2009, p. 879).

Complex adaptive systems are systems that consist of entities that adapt their behavior or learn from it in response to interactions with other entities (Holland, 2006). Agents are entities that are goal-oriented and adaptive, meaning they seek to maximize some value assigned to them and learn what actions to take to increase that value (Weidlich and Veit, 2008). What makes agents "more useful than equations-based methods in a world of multiple possible futures [is] partly because they are built synthetically 'from the bottom up" (Batten, 2009, p. 200). ABM typically consists of software agents with certain goals that interact in a simulated environment with the purpose of gaining insight from the emergent behavior that develops. With respect to technological change and contrasted to optimization approaches "ABM is no longer the result of long-term strategic planning, but the result of agents' reacting and adaptive behaviors" (Ma and Nakamori, 2009, p. 874). A possible use of ABM simulations is as a virtual laboratory to conduct experiments on how a system reacts to certain interventions. With respect to ABM in a policy making context, being able to monitor how a network of multiple heterogeneous agents evolves based on the implementation of different policy instruments gives policy makers the potential to assess the effects of those instruments in ways not possible to do in real life (Beck et al., 2008).

With traditional modeling tools one is forced to make what North and Macal (2007, p. 4) call "heroic assumptions" to reduce the detail and interactions between components in a system. By assuming that a system consists of homogenous perfectly rational agents one can miss the details and transients that occur along a system's evolution. Another complication of making heroic assumptions is that they can be "used to make up for missing data" (North and Macal, 2007, p. 5). With the proliferation of databases, data taking sensor networks, and the increasing availability of open data sources one is instead faced with a data deluge and need no longer make heroic assumptions to cover for a lack of information. Although optimization tools may also be able make use of more data the increased computational needs required to incorporate the detailed data limit the usefulness of the additional data in traditional modeling tools. Now that one has access to highly detailed data Lee's complicatedness criticism of models being based only on large interactions between system components while ignoring the smaller ones can be addressed and, for the reasons detailed above, the technique that is naturally capable of addressing it is ABM. In response to Lee's wrongheadedness criticism, an ABM's structure is not set statically from the beginning but rather evolves in response to interactions at the lowest component levels so that the model's behavior is a direct consequence of the simple equations that determine each agent's behavior.

Of course ABM is not suited for all problems or domains. The outputs an ABM produces are not optimal solutions but the result of the emergent interactions among agents. Areas where a single actor is the dominant decision making entity would be better suited for analysis by optimization approaches. This goes back to the problem statement where it was argued that different types of modeling methods were needed to study DG because more actors are getting involved in the decisions affecting changes in energy systems. It makes sense to use optimization models to help with decisions to invest in large multi-million dollar coal fired power plants for example. The effects of bounded rationality do not play as much of a role in those types of decisions so models employing attributes of neoclassical economics like utility maximization are likely to provide the best solutions. In general, problem domains in the physical sciences are less likely to be appropriate for ABM. For example, one would not use an ABM to determine the routing of electrical lines on a circuit board since physical constraints determine the best routing paths. On the other hand, it would be suitable to use an ABM to explore the best traffic routing paths through a city center since traffic patterns are influenced by both physical and social constraints.

4. DISTRIBUTED GENERATION MODELS

Already, the application of agent-based models in electricity market dynamics is generating increasing research interest and has warranted several surveys. Zhou et al. (2009) survey several of the tools used for such models while Weidlich and Veit (2008) review models that are concerned with market structure and market design. ABMs related to the deployment of DG in energy infrastructures, while not as developed as ABM of electricity market dynamics, is an increasing area of interest. The following papers cited in this section show the state of ABMs in the DG deployment domain. These models have shown the ability of ABM to provide useful insight into DG transition problems that is of a different nature than what is produced from optimization approaches.

An ABM of introducing biomass to South Africa's energy network is carried out by Beck et al. (2008). Their goal was to determine how to define a preferred energy network and how to identify interventions toward a preferred future. In doing so they claim to have developed a new approach to integrated resource planning. What they do is combine a global perspective, using dynamic multi-objective optimization (DMOO), with a distributed perspective, using ABM. They then see what the differences are between the approaches by applying them to a case study of a power generation system in South Africa. They find that ABM combined with another approach is useful since it can identify "a range of policy instruments, which can stimulate innovation - both in terms of technology development, but also in terms of agent behavior" (Beck et al., 2008, p. 2805). They find that the combined approach of using both DMOO and ABM deals with the shortcomings of either one compared to using them by themselves.

The socio-technical complexity of energy infrastructures is the focus of the paper by Houwing et al. (2006). They investigate how the large-scale adoption of decentralized energy technologies can be conceptualized based on a complex systems approach. The argument is that DG has previously been treated in the literature as an individual technology but if, as the authors assume, it is headed for widespread adoption then it needs to be treated as part of a complex socio-technical system. The introduction of DG will lead to many new challenges in the areas of energy balance, electricity trade and its affect on ancillary infrastructures like gas and heat. Since the influence of DG on decision-making, operation and performance of actors is not known a simulation that provides insight into these areas is in order. A framework for modeling households with DG is proposed and then reasons to use ABM for the simulations is given. The results are a way to model households with DG and a proposal is made for some questions to look into for those that wish to model DG with ABM. The authors state that preliminary results of their modeling are promising.

The diffusion of micro-CHP systems was explored in an ABM by Faber et al. (2010). They looked into the effectiveness of different subsidy schemes on the spread of micro-CHP installations in the Netherlands. The consumer agents in their model choose between buying a traditional condensing boiler heating unit for their homes and a micro-CHP unit based on least cost. The subsidy levels on micro-CHP are varied by subsidy levels per unit and by total amount of subsidy given out. The results indicate that it costs less to increase the market share of micro-CHP by having a higher subsidy that is limited by a fixed overall subsidy budget than to have a lower subsidy with an unlimited subsidy budget. The model is positioned as a novel tool for policy analysis that is adaptable as new information becomes available.

Wittmann (2008) has also modeled the diffusion of DG technologies using ABM techniques. The model is highly detailed and is designed to show the evolution of an urban energy system when both residential and commercial agents replace their heating systems over time. The agents' behavior is based on survey data splitting them into technology leader, traditional and established agent types. Within these types their decision making is further differentiated among levels of rationality employed. These highly specified agent types give the model the ability to show diffusion curves broken down by agent behavior for the nine different heating technologies in the model. For policy makers and technology manufacturers, knowing what consumer types have a propensity for a certain technology could lead to making the introduction of a new technology more effective through the tailoring of policies and marketing.

Finally, the work of an author of this paper, Veneman (2011), shows the promise of ABM to provide insights into what drives changes in how DG is deployed. The model compares the diffusion of DG technologies in competition with electricity supplied by the grid. The energy consumer agents each have attributes that concern how the different energy sources satisfy four different needs related to cost, environment, social identity and technology preference. The decision making of an agent is governed by their relative uncertainty surrounding how their energy source is helping to meet these needs. Agents are able to choose new energy sources periodically throughout the simulation and depending on their decision making mode the agents then choose the energy source that will best meet their needs. By accounting for more than just economic criteria the model allows for one to see how an agent's social situation and environmental concerns can impact the deployment of new products like DG. The simulations show the differences in energy source choices across a range of energy price and economic development scenarios. The use of ABM in this case enables the model to perform what-if evaluations of energy system developments across uncertain futures as well as explore drivers behind the changes.

5. WHAT CAN BE IMPROVED AND AREAS FOR FURTHER RESEARCH

One of the deficiencies of ABM in this context is the lack of empirical data to compare the results of the models with. This deficiency has not escaped the notice of other researchers involved with ABM and some steps to account for it are being proposed. While it is recognized that "because of the large number of theoretical models developed, there is more confidence that ABM is a valid technical methodology that can provide novel insights to scientific inquiry" (Janssen and Ostrom, 2006, p. 2) there is still a need to combine empirical methods with ABM. Janssen and Ostrom (2006) provide an approach to do so via case studies, stylized facts, role games and laboratory experiments. The combination of these methods with ABM are needed "to understand crucial components of ABMs, such as social interactions and the diffusion of knowledge and information" (Janssen and Ostrom, 2006, p.

10). Anderson (1999) outlines an approach to using empirical data in a complex adaptive systems model that would be applicable to these models. The use of more empirical data in ABM would serve to increase their validity and application.

Stronger validation and more discussion about it would also help to increase confidence in ABMs in this context. Of the models mentioned in the previous section only the one by Veneman (2011) has any significant discussion on validation employed during model development. Since empirical validation of forecasting models is difficult, Moss (2008) details some approaches that agent-based modelers can take to conduct validation on their models. An overview of the validation efforts performed on the EMCAS model is given in Macal and North (2005). The EMCAS modelers took many steps including data validation, subject matter expert judgement and invalidation exercises to "establish credibility for the EMCAS model and its results for use in practical decision making" (Macal and North, 2005, p. 1). With this growing body of literature on how to do validation on ABMs it is now up to the researchers designing these models to generate more discussion so that decision makers can be confident in the use of them for policy making.

The models reviewed in this article all contain only continuous DG sources like micro-CHP so there exists an opportunity to expand them to incorporate discontinuous sources such as wind and solar generators. Some of the information necessary to allow for discontinuous sources in the model would be electricity time of use information showing demand changes throughout the day and, at a minimum, hourly solar and wind availabilities. Another way to incorporate other types of generators would be to aggregate them as virtual power plants (VPP) that combine continuous and discontinuous DG with information systems technologies in order for a group of DG to act in a similar manner as large energy generators. The use of VPPs in the model would help to manage the issue of discontinuous output from other types of DG.

New insights may come from comparing an agent-based DG deployment model with models and case studies from other domains as well. Since these models consider consumer behavior a natural comparison would be that of empirical studies on how consumer behavior impacts the launch of new products. A comparison could be made between the diffusion curves of this model and those of other disruptive products (e.g. digital cameras, cell phones, etc.). Examining the differences between these curves could yield a deeper grounding of the parameters and formulas used to produce the other DG models.

6. CONCLUSION

The drivers for using ABMs for investigating the impacts of the deployment of DG have been detailed. It was argued that due to the complex socio-technical interactions in these systems the development and use of modeling methods, like ABM, that account for the emergent behavior present within these systems are worth exploring for decision makers looking to gain further insight into their domain. The drawbacks of using traditional modeling approaches for the study of DG deployment were elucidated. A review of ABMs specifically related to DG deployment was conducted. Finally, suggestions were made for further research and improvements to ABMs of DG deployments.

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