Environmental Modelling & Software 70 (2015) 163–177

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

# Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors

Varun Rai [a, b, *], Scott A. Robinson [a, c]

[a] LBJ School of Public Affairs, The University of Texas at Austin, USA
[b] Department of Mechanical Engineering, The University of Texas at Austin, USA
[c] Jackson School of Geosciences, The University of Texas at Austin, USA

ARTICLE INFO

*Article history:*
Received 7 September 2014
Received in revised form
26 February 2015
Accepted 23 April 2015
Available online 16 May 2015

*Keywords:*
Agent-based modeling
Solar photovoltaic (PV)
Complex systems
Technology adoption
Social networks
Bounded rationality

ABSTRACT

Agent-based modeling (ABM) techniques for studying human-technical systems face two important challenges. First, agent behavioral rules are often *ad hoc*, making it difficult to assess the implications of these models within the larger theoretical context. Second, the lack of relevant empirical data precludes many models from being appropriately initialized and validated, limiting the value of such models for exploring emergent properties or for policy evaluation. To address these issues, in this paper we present a theoretically-based and empirically-driven agent-based model of technology adoption, with an application to residential solar photovoltaic (PV). Using household-level resolution for demographic, attitudinal, social network, and environmental variables, the integrated ABM framework we develop is applied to real-world data covering 2004–2013 for a residential solar PV program at the city scale. Two applications of the model focusing on rebate program design are also presented.
© 2015 Elsevier Ltd. All rights reserved.

## 1. Introduction

Development of methods that better represent the bounded rationality of economic agents (Gigerenzer and Selten, 2002), largely arising due to heterogeneous information sets and heuristic decision-making (Conlisk, 1996), is important for better understanding of the emergent phenomena that permeate economic systems (Rubinstein, 1998; Sawyer, 2005). In this vein, recent years have seen a spurt in the use of agent-based modeling (ABM) in a range of economic and human-technical systems, including transportation (Wang, 2005), land use (Evans and Kelley, 2004; Robinson and Brown, 2009), market structure (Heppenstall et al., 2006; Kirman and Vriend, 2001), transaction costs (Zhang et al., 2011), strategic interactions in climate policy (Brede and De Vries, 2013; Gerst et al., 2013), and technology adoption (Schwoon, 2006), especially that of environmentally-friendly technologies (Cantono and Silverberg, 2009; Gunther et al., 2001; Laciana and Rovere, 2011; Lee et al., 2014; Mazhari et al., 2011; Schwarz and Ernst, 2009; Tran, 2012; Van Vliet et al., 2010; Zhang and Nuttal, 2012). ABM is attractive to researchers interested in studying the evolution of complex human-technical systems because of the flexibility afforded by ABM to describe in great detail the behavioral as well as structural (policy; prices; infrastructure) aspects of the system. However, ABM techniques for studying human-technical systems face two important challenges (Durlauf, 2012; Windrum et al., 2007). First, agent behavioral rules in agent-based models are often *ad hoc* – they do not necessarily build upon systematic theories of behavior, thereby making it difficult to assess the implications of these models within the larger theoretical context (Durlauf, 2012; Feola and Binder, 2010). Second, the lack of relevant empirical data precludes many models from being appropriately initialized and validated against real-world data (Heppenstall et al., 2006); this limits the value of such models for exploring emergent properties or for policy evaluation. Thus, careful development of agent behavioral model and of rich datasets and methods to enable robust initialization and validation of agent-based models is important.

### 1.1. Objectives

Our objective in this paper is to present an agent-based model of technology adoption that systematically tries to address the

* Corresponding author. 2315 Red River St., LBJ School of Public Affairs, The University of Texas at Austin, TX 78712, USA.
*E-mail address:* raivarun@utexas.edu (V. Rai).

http://dx.doi.org/10.1016/j.envsoft.2015.04.014
1364-8152/© 2015 Elsevier Ltd. All rights reserved.

challenges identified above regarding the theoretical and empirical components of ABM. Using a uniquely rich and comprehensive dataset covering 2004–2013, we build an agent-based model of the adoption of residential solar photovoltaic (PV) systems in the city of Austin (Texas, USA), which has a population of approximately 900,000. In addition to an empirically driven agent-interaction model and a theoretically-driven behavioral model, we also account in great detail for the physical environment (irradiation, tree cover, home size) and economic features (prices, subsidies, wealth) that impact agent behavior, again using empirical data. We present a detailed step-by-step construction of the different components of the agent-based model, the process of initializing the model, and setting up of the model parameters and variables in accordance with the theoretical and empirical underpinnings of the system. We also present methods for temporal and spatial validation of the model along with the fitting and validation results. The emphasis is to provide a high level of detail in the construction of the behavioral model, data integration, and initialization procedures. These details, which are critical to making the model reproducible, are often neglected (Grimm et al., 2010). Because agent-based models intended for policy evaluation, predictive modeling, or the study of emergent phenomena must go through rigorous model set-up and empirical grounding, we hope that this paper will help facilitate the development of agent-based models for energy technology adoption in a more empirically-grounded fashion.

### 1.2. Applications

A key motivation in developing this framework is to allow for a range of policy simulations that could inform decision-making of policymakers and utility planners. To illustrate this potential, in Section 4.2 we present two applications of the ABM framework developed here. These policy scenarios are based on the following more general questions of central importance to the designers of solar programs, but the framework is generalizable across a suite of technologies.[1]

#### 1.2.1. Subsidy program design

*Low-Income Solar Programs*: Adopters of PV tend to be much wealthier than average (Rai and McAndrews, 2012). This finding has raised equity concerns in relation to publicly-funded rebates. Programs like California's Single-Family Affordable Solar Housing Program were created to address these concerns, but high cost and long time-frames associated with solar PV adoption limit the ability of program designs to experiment with different rebate offerings. Using the framework developed here a range of *targeted rebate* scenarios could be explored through ABM simulation experiments.

*Rebate Levels and Adoption*: Recent empirical findings on optimal subsidy design suggest that when peer effects and learning-by-doing effects are strong rebates should be front-loaded in order to maximize adoption – larger rebates early on in the subsidy program and declining over time are found to be more cost effective (Dong, 2014; Van Benthem et al., 2008). These aggregate findings could be validated in full-scale ABM simulations including two- or multi-tiered rebates and by varying the rate at which the tiered rebates change over the lifetime of a solar program. The key outcome of interest is the elasticity of PV adoption: (i) what is the impact of changes in rebate level on PV adoption at the population-scale? and (ii) how does this impact change with the underlying installation base?

### 1.3. Main contributions

The main contributions of this paper are: (i) development of a theoretically and empirically grounded integrated model for consumer technology adoption, applied to residential solar PV, (ii) highly granular description of the system, including behavioral, social, and physical-economic environmental aspects at the household level, (iii) development of new techniques to achieve a population-wide, household-level empirical initialization, (iv) development and application of multiple (temporal, spatial, and demographic) external validation metrics, and (v) application of the developed model for two ABM simulation experiments to explore solar program design.

## 2. Background and related literature

Advances in computing power combined with the increasing availability of granular data have enabled researchers to apply ABM for analyzing a diverse set of problems (An, 2012; Matthews et al., 2007). A particular area of growth in ABM applications has been to model consumer technology adoption, a problem for which standard methods include conjoint analysis (Eggers and Eggers, 2011; Green and Srinivasan, 1978), Bass diffusion models (Islam, 2014; Islam and Meade, 2012; Shi et al., 2014), and dynamic discrete choice (DDC) models (Berry, 1994). Modeling of consumer energy technology adoption is particularly challenging because the nominal economics (price) of the technology is only one determinant of consumers' likelihood to adopt. Other behavioral and social phenomenon such as decision heuristics, anchoring, path-dependence (past experiences), risk aversion, trust-based information networks, and social norms are also quite important in understanding energy-related consumer decision-making (Dietz et al., 2013; Graziano and Gillingham, 2014; Kemp and Volpi, 2008; Margolis and Zuboy, 2006; Stern, 1992; Wilson and Dowlatabadi, 2007). DDC models are among the most sophisticated approaches for analyzing consumer choice (McFadden, 2001). Unlike conventional conjoint analysis, DDC models have a time component (multi-period), allowing to factor intertemporal tradeoffs. Unlike Bass diffusion models, the unit of analysis in DDC models is the individual, thereby allowing the direct study of individual decision-making processes on system outcomes. However, these predominant methods for modeling consumer technology adoption often rely heavily on assumptions of utility maximizing actors who have rational expectations about the future technological trajectory. Furthermore, there are several other key challenges associated with the representation of important behavioral, social, and spatial phenomena in conventional models of energy technology adoption (see the review in Kemp and Volpi, 2008).

While the potential of ABM to address the weaknesses of conventional diffusion models is quite promising, it is important that ABM development for the study of human-technical systems follow fundamentally sound principles (Durlauf, 2012; Grimm et al., 2005; North and Macal, 2007; Rand and Rust, 2011; Smajgl and Barreteau, 2014). In particular, agents' decision rules (Durlauf, 2012), the empirical basis of the system description (Bohlmann et al., 2010; Parunak et al., 1998; Smajgl et al., 2011; Sopha et al., 2013), and model validation (Fagiolo et al., 2007; Heppenstall et al., 2006; Werker and Brenner, 2004) demand rigorous treatment. This is especially important if policy evaluation or predictive modeling is the main objective. Though not always followed in practice, the need for empirical basis and validation in ABMs has been

[1] Our framework may be applied not only to solar PV but also to a range of other consumer technologies. We provide the applications for the design of solar programs because the empirical components of our model are trained on granular data from a solar program. Similar data on other technologies would enable studying the adoption of those technologies as well. Furthermore, although not considered in this paper, other simulation experiments could include exploration of different information seeding strategies and location-based rebate targeting.

Download English Version:

https://daneshyari.com/en/article/6963142

Download Persian Version:

https://daneshyari.com/article/6963142

Daneshyari.com