Environmental Modelling & Software 92 (2017) 261–268

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

Automating agent-based modeling: Data-driven generation and application of innovation diffusion models

Thorben Jensen [a, b, *], Émile J.L. Chappin [a, b]

[a] Wuppertal Institute for Climate, Environment and Energy, P.O. Box 100480, 42004 Wuppertal, Germany
[b] Delft University of Technology, P.O. Box 5015, 2600 GA Delft, The Netherlands

ARTICLE INFO

Article history:
Received 21 July 2016
Received in revised form
5 February 2017
Accepted 20 February 2017

Keywords:
Agent-based modeling
Automated model generation
Diffusion of innovations
Data-analysis tool
Policy simulation

ABSTRACT

Simulation modeling is useful to understand the mechanisms of the diffusion of innovations, which can be used for forecasting the future of innovations. This study aims to make the identification of such mechanisms less costly in time and labor. We present an approach that automates the generation of diffusion models by: (1) preprocessing of empirical data on the diffusion of a specific innovation, taken out by the user; (2) testing variations of agent-based models for their capability of explaining the data; (3) assessing interventions for their potential to influence the spreading of the innovation. We present a working software implementation of this procedure and apply it to the diffusion of water-saving showerheads. The presented procedure successfully generated simulation models that explained diffusion data. This progresses agent-based modeling methodologically by enabling detailed modeling at relative simplicity for users. This widens the circle of persons that can use simulation to shape innovation.

1. Introduction

Understanding the prospects of innovations and how they spread is powerful. Mechanistic understanding of the diffusion of an innovation can help explaining their success. For instance, the Theory of Diffusion of Innovations by Rogers (2003) allows understanding diffusions based on general mechanisms of interpersonal interactions. From these, it is possible to infer general patterns and key actors of innovation diffusion. Further, the explanatory power of the general mechanisms of innovation diffusion has been confirmed in empirical cases of diffusing innovations (Schwarz and Ernst, 2009; Sopha et al., 2013).

Beyond understanding, found mechanisms can be used for guiding practical actions. Persons and organizations often want to know *"how to speed up the rate of diffusion of an innovation"* (Rogers, 2003). Actions that achieve this can directly be derived from causal mechanisms of the spreading of an innovation. Further, simulation can be used to project and estimate the impact of practical actions. This allows forecasting the impact of these actions from the underlying mechanisms. This paper will focus in particular on simulating innovation diffusion with agent-based modeling (ABM). This approach represents real-world actors with computer agents, whose actions towards innovations are modeled by explicit decision models (Delre et al., 2007; Jensen and Chappin, 2017).

However, mechanistic understanding is particularly challenging to gain. It is harder to achieve than statistical inference, which reveals co-occurrence of events in a set of observations. Requirements for gaining it also exceed sole causal understanding, which 'only' requires knowing that one event generally causes another one (Aalen and Frigessi, 2007). Instead, mechanistic understanding implies to know if one event (likely) *"leads to a specific, deterministic behavior in another"* (Leek and Peng, 2015).

ABM can illuminate mechanisms of the diffusion of innovations, but is challenged by time and labor intensive model building (van Dam et al., 2012). Via simulation, ABM links micro-level actions of actors to 'emergent dynamics', e.g. innovation diffusion (Chappin and Dijkema). Thereby, macro-dynamics of innovation diffusion are 'decoded' by being explained by micro behavior of agents (Grimm et al., 2005; Stern, 2016). Unfortunately, ABM is commonly more time-intensive than its alternatives (e.g. system dynamics (Watts and Gilbert, 2014) and statistical analysis). This limits its practical applicability. In line with these challenges, Garcia and Jager (2011)

* Corresponding author. Wuppertal Institute for Climate, Environment and Energy, P.O. Box 100480, 42004 Wuppertal, Germany.

E-mail addresses: Thorben.Jensen@wupperinst.org (T. Jensen), E.J.L.Chappin@tudelft.nl (É.J.L. Chappin).

URL: http://thorbenjensen.de, http://chappin.com/emile

http://dx.doi.org/10.1016/j.envsoft.2017.02.018
1364-8152/

emphasize the current *"challenge of defining AMSs (i.e. agent-based simulation models) that are useful (to) managers without programming skills."*

We propose to enable agent-based modeling to overcome these limitations by automated model generation. Several approaches to automation exist, which we propose to combine: (1) Translating simple specifications into executable models. Examples are http://m.modelling4all.org and the MAIA framework (Ghorbani et al., 2013), which automatically generate simulation models from specifications by domain-experts. (2) Model building from existing components. A methodology for this idea is 'TAPAS',[1] via which previously validated models are reused for new applications (Frenken, 2006). (3) Using data for model-building in a structured way. Grimm et al. (2005). proposed 'Pattern-oriented Modeling' to falsify model variants that fail to reproduce a set of patterns from empirical data. This replaces ad-hoc decisions and informed guesses about adequate model structures and parameters with rigid testing against empirical data.

Therefore, the target of this study is to present a process that systematically builds ABMs via the following steps: (1) extracting driving mechanisms from empirical observations on innovation diffusion; (2) projecting diffusions into the future; and (3) assessing the effects of real-world actions and policies ex-ante, via simulation. This study aims to answer the following question: *"Can automated generation of agent-based models on the diffusion of innovation be achieved, and how could this be useful?"* This question will be addressed by specifying an automated software procedure for this task. To further provide *proof of concept*, application of an implementation of this procedure to the diffusion of sustainable products among households will be presented.

The remainder of this paper is structured as follows. First, we provide background on agent-based modeling of the diffusion of innovations. Second, the procedure that automates the building of such models is presented. Finally, this procedure is applied to a case of innovation diffusion.

2. Agent-based modeling of innovation diffusion

This section will provide details on agent-based modeling of innovation diffusion, which is the application domain of the proposed automation procedure. We will show that there exists a high degree of standardization of existing diffusion models. This standardization helps automated modeling.

According to Geels and Johnson (2015), there exist four general types of dynamic innovation diffusion models. We hereby focus on innovation models that are dynamic, because innovation itself is a process of change (Kiesling et al., 2012). (1) *Adoption models* capture spreading of an innovation among potential adopters, e.g. how the user base of a new product increases via word-of-mouth. (2) *Models of up-scaling and system building* describe a small system expanding to a larger one, e.g. an electricity system expanding from a decentralized ones to a single centralized system. (3) *Replication and circulation models* emphasize the replication of an adoption during its circulation to other location. Considering replication emphasizes adapting an innovation to other local conditions. (4) *Societal embedding models* consider the embedding of an innovation in business, societal, policy, and user environments.

'Adoption' type models are of special interest to this study. This is because their modeling of *"independent adopters making (adoption) decisions"* (Geels and Johnson 2015, p.12) fits well with the actor-centric perspective of agent-based modeling. Adoption type models are represented by 'aggregated' and 'individual level' models (Kiesling et al., 2012). Aggregated models directly model the overall adoption dynamics of an entire population. This approach is represented by the 'Bass model' and commonly modeled with system dynamics (Kiesling et al., 2012). Conversely, 'individual level' models capture the adoption decisions of individuals in a population, from which overall adoption dynamics 'emerge'.

In this study, we will focus on the individual level models, because of their capability to incorporate more aspects of reality. According to Kiesling et al. (2012), 'individual level' models are superior to 'aggregated' ones (such as system dynamics). (1) *Explanatory power* is greater for 'individual level' models, because they explicitly connect behavior and decisions of agents with aggregated diffusion dynamics. (2) *Population heterogeneity* can be captured more detailed in 'individual level' models. (3) *Social processes* (e.g. interactions between consumers) are modeled explicitly. This process can have great impact on diffusion success (Delre et al., 2007). Agent-based 'individual level' models are particularly suited to model social interactions. In contrast to discrete-event simulation, they are capable of modeling detailed social interaction topologies in a computationally efficient way (Watts and Gilbert, 2014). Consequently, this study will focus on innovation diffusion models that are agent-based.

Automating the building of agent-based innovation diffusion models is facilitated by their similar structure. A review by Kiesling et al. (2012). finds that most 'individual level' diffusion models have such a common structure. Accordingly, virtually all agent-based innovation diffusion models are variations of one *meta-model*, shown in Fig. 1. This meta-model comprises the following elements: (1) Consumer agents represent the entities than can adopt an innovation. These can be individual persons, households, or groups of households. (2) Social structure is the heterogeneity of consumer agents, e.g. dividing them in different consumer groups. (3) Decision making processes (formalized as *decision models*) are the key actions of consumer agents to model the adoption of an innovation. (4) Social influence between agents (from peers, social groups or overall population) can affect decision making of consumers and is commonly modeled as a social network graph. This overall similarity simplifies automated model generation. This is because there is less variation in input data and less structural variation than needs to be considered.

3. Methods

In this section, we will present in detail the automation procedure to building agent-based models on innovation diffusion. We regard this approach as innovative, because it meets a previously

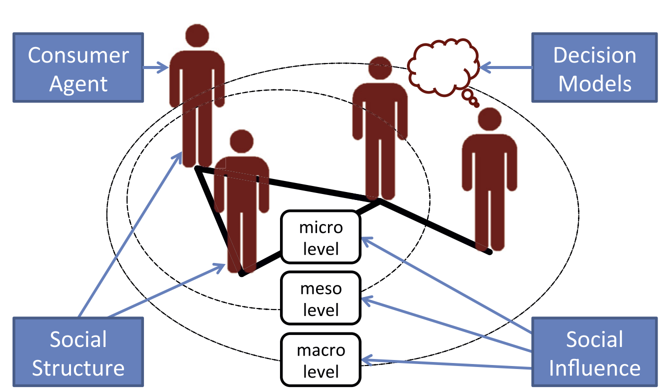

Fig. 1. Meta-model of agent-based models of innovation diffusion. Based on review by Kiesling et al. (2012, Fig. 3).

[1] 'TAPAS' abbreviates "Take A Previous model and Add Something".