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## A procedure for innovation diffusion models

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# Automated model structure variation and policy robustness testing: a procedure for innovation diffusion models

Thorben Jensen[*a,b], Georg Holtz[a], Emile Chappin[b,a]

a. Wuppertal Institute for Climate, Environment and Energy, Germany
b. Delft University of Technology, the Netherlands
[*] Corresponding author, T.Jensen@tudelft.nl

## Abstract

In this paper we present a procedure that enables a systematic and partially automated parameterization and selection of agent-based models of the diffusion of innovations and policies to support diffusion processes. A prototype on the diffusion of water saving shower heads is presented. Our results suggest that the presented approach can adequately and systematically evaluate different sets of parameters and model structures against known diffusion data.

## Introduction

When developing agent-based models, limited knowledge of the target system and lack of data often cause uncertainty about how to specify certain aspects of the model. In order to nevertheless derive robust policy advice from models, the effect of proposed policies then has to be simulated and assessed across a range of model specifications that, in sum, reflect the range of plausible representations of the real world system. Uncertainties about model specification concern both, parameter values but also about aspects of the model structure such as plausible decision models of agents [1]. Sensitivity analysis is a method to address uncertainty about parameter values and is a standard part of almost every modeling exercise [2]. Furthermore, approaches have been developed to test a variety of model structures against empirical data and to select out of a bigger set only those structures that are in accordance with empirical data [3]. However, variation of a model's structure is a time consuming exercise and therefore often not done. Even more so, testing a range of policies against a set of model structures (and a set of parameter values for each model structure) and comparing the effects of policies against this broad set of model specifications is a time consuming and cumbersome exercise.

In this paper we present a procedure to accelerate this process for models of the diffusion of innovations, by making the process transparent and do a systematic variation and selection process. Part of this process is automated, in order to develop models and assess policies at greater speed than is current practice.

## Innovation diffusion models

According to Rogers [4] the diffusion of an innovation is the process by which an innovation is communicated through certain channels over time among the participants in a social system. Most 'micro level' diffusion models that aim to represent this process have a common structure [5]: (1) Consumer agents define the individual entities than can adopt an innovation. This 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 are the key actions of consumer agents to model the adoption of an innovation. (4) Social influence between agents often affects decision making processes and is commonly modeled as a social network graph. Models vary in the range at which social influence is exceeded. This can be influence from direct peers, from the respective social group or the entire population of agents. All these ranges of influence can be modeled as a social network graph.

## Automation procedure

As depicted in figure 1, the presented automation procedure comprises three phases: preprocessing, inverse modeling, and policy simulation. It has been implemented in NetLogo.

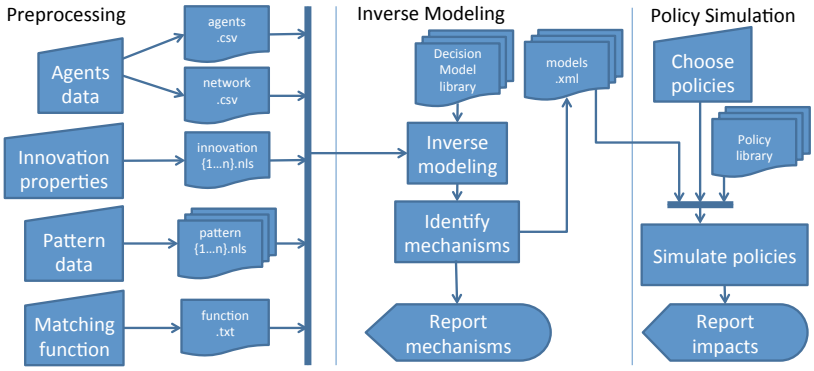


**Figure 1**: Overview of automation procedure (see text for details).

*Preprocessing:* In this step, input data is provided to specify those model elements that are not selected to be varied, and to define empirical data based on which model variations will be selected or discarded. In our specific modeling exercise, agents are each defined by their numerical ID, their 2D coordinates, and the group they belong to. The attribute 'group' serves to capture heterogeneity of agents and allows decision models to differentiate adoption decisions between actors. The social network is provided by tuples of each an agent that influences another agent. Furthermore, for each innovation the properties 'environmental friendliness', 'ease of use,

‘compatibility’, ‘savings from innovation’ and ‘ease of installation’ [6] are defined as number in [0,1], which represent how an innovation is perceived by households. Finally, ‘patterns’ are provided that characterize the dynamics of the real-world process that shall be modeled. These patterns are ‘indicators of essential underlying processes and structures’ [3]. Each additional pattern reduces uncertainty about which mechanisms could explain the diffusion of an innovation. An example for a pattern is the exponentially increasing adoption share of a successful innovation during its initial diffusion [4]. Further, a ‘matching function’ is defined that compares the simulation outcome to the empirically identified patterns.

*Inverse modeling:* In this automated phase, simulations are conducted with a range of model variations that have to be defined beforehand. In the experiments reported below we have varied the decision models of agents between four decision models (cf. figure 1, ‘Decision model library’). For each model variation the parameter setting that satisfies the matching function best is identified. We have used the *BehaviourSearch*[1] extension of NetLogo with a simulated annealing optimization to implement this step. Based on the results of this optimization and comparison with patterns, model variations are selected for further processing or discarded.

*Policy simulation:* Policies were implemented as NetLogo functions and stored as individual ‘NetLogo source files’. In this step they can be selected by the user to test their effect for the set of model variations that were found plausible in the inverse modeling phase. With the *BehaviourSpace* tool in NetLogo, policy are assessed automatically, based on each plausible model specification.

## Application case: diffusion of water-saving appliances

As a proof of concept and for illustrating the presented automation procedure, we apply the procedure to the diffusion of water-saving showerheads as presented by Schwarz [7].

During *preprocessing*, we defined three agent groups (so-called leading lifestyles, mainstream households, and hedonists). Two patterns on the diffusion of water-saving showerheads where identified in the available empirical data [7]: 1) Market shares in Germany in the year 2005, after ca. 15 years of diffusion, differentiated by consumer groups; 2) The exponential shape of the adoption diffusion curve during these first 15 years of innovation diffusion.

For *inverse modeling*, we defined and tested four decision models. First, we defined a model based on the one proposed by Schwarz [7]. In Schwarz’ model, agents either decide to adopt the appliance, or decide according to the majority of their peers. We added some flexibility to this model through providing ranges to parameter values that were fixed in the original model.[2] This resulted in the ‘Schwarz flexible’ model. Second, we defined a model based on the Theory of Planned

[1] http:www.behavioursearch.org

[2] In our model the deliberation rate may range in [0.004,0.04] and the probability for each consumer group to adopt according to majority of peers is flexible in [0,1].

Behaviour [8], the TPB model. In this model attitude and influence from peers are weighted and added to derive the agents decision. Both models assume that agents can deliberate about adoption at all times. We differentiated both models by the option of an additional word-of-mouth (WOM) mechanism. If this mechanism is active, agents only consider adopting feedback devices if they are 'aware' of them. They become aware once a peer adopts the device. Figure 2 shows the results of the inverse modeling for the four model variations. Results show that the 'Schwarz flexible (no WOM)' model was not able generate an exponential pattern. The 'TPB (no WOM)' model was not able to match the adoption data at the same time as the exponential pattern. Therefore, these two models were discarded, and the two models 'Schwarz flexible (WOM)' and 'TPB (WOM)' were selected for policy simulation.

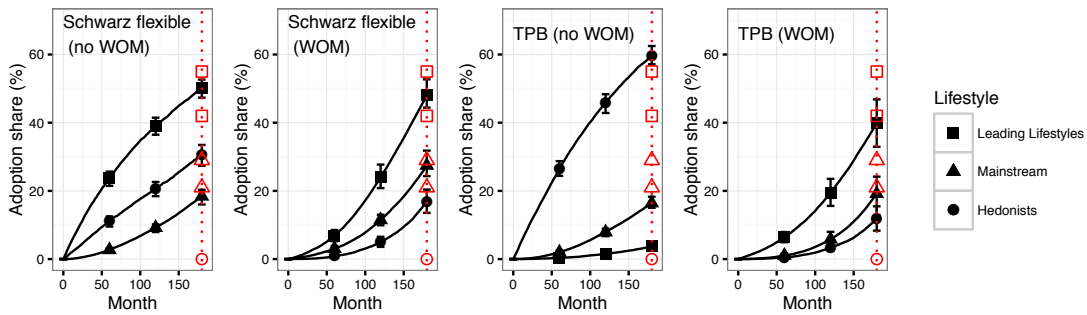


**Figure 2.** Average adoption of water-saving showerheads, as simulated by the four tested models at best fitting parameters. Results are differentiated by consumer group. The hollow points show empirical market shares after 15 years of diffusion.

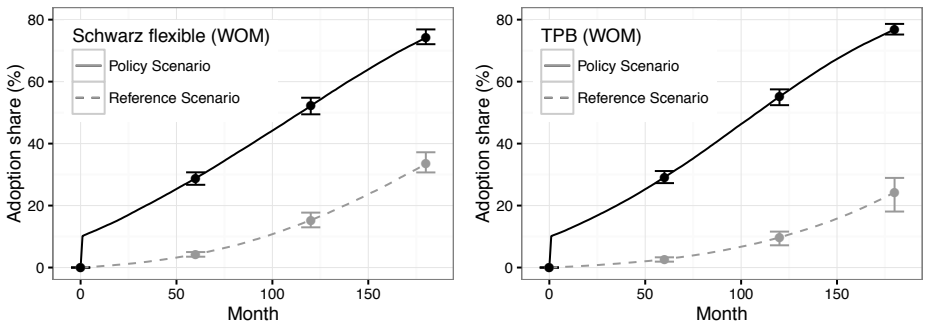


**Figure 3**: Results of policy for the two selected model variants.

For *policy simulation*, we designed a simple marketing strategy of giving away free products to 10% of households at the beginning of the simulation. Figure 3 shows the results of this policy for the two selected model variations. Impacts of the policy are quite similar for both models: the innovation (initially) spreads at a much quicker pace and the amount of additional adoptions within 15 years is similar, too. This adds supports the conclusion that the policy is robust against the remaining uncertainty about the decision model.

## Discussion and conclusions

The experiments reported in the previous section demonstrate the feasibility of the presented automation procedure. We argue that implementing such a procedure has several benefits: 1) It makes tests of model variants regarding their ability to reproduce empirical facts easier. Doing so, it supports an improvement of validity of models, 2) It facilitates to test policy recommendations against a range of plausible model variants and thus supports the identification of robust policies, 3) It makes these features available for quick applications of models to new cases (e.g. simulating the diffusion of a product in a different city) independent of the availability of a modeling expert. Once the model variants and polices are implemented, a user could select and test model variants without requiring highly developed modeling or simulation skills. Skills in data processing are however required to process and provide the required input data.

We have developed this procedure for the case of innovation diffusion models. This is an arguably uncomplicated case. The similarity of the structure of various innovation diffusion models simplifies automating the building of agent-based models of innovation diffusion, as the same basic ontology holds for many model variations. This similarity makes the definition of interfaces between decision models, agents, innovations and policies comparably easy. We propose to apply the presented automation procedure to other cases in which model variants are less similar in order to explore how far automation of the generation of agent-based models can be extended.

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