

Scheller, Fabian; Johanning, Simon; Bruckner, Thomas

Research Report

IRPsim: A techno-socio-economic energy system model vision for business strategy assessment at municipal level

Beiträge des Instituts für Infrastruktur und Ressourcenmanagement, No. 02/2018

Provided in Cooperation with:

Institute for Infrastructure and Resources Management, University of Leipzig

Suggested Citation: Scheller, Fabian; Johanning, Simon; Bruckner, Thomas (2018) : IRPsim: A techno-socio-economic energy system model vision for business strategy assessment at municipal level, Beiträge des Instituts für Infrastruktur und Ressourcenmanagement, No. 02/2018, Universität Leipzig, Institut für Infrastruktur und Ressourcenmanagement (IIRM), Leipzig

This Version is available at:

<https://hdl.handle.net/10419/183217>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



UNIVERSITÄT LEIPZIG

Wirtschaftswissenschaftliche Fakultät
Faculty of Economics and Management Science

IRPsim: A techno-socio-economic energy system model vision for business strategy assessment at municipal level

Fabian Scheller, Simon Johanning, Thomas Bruckner

02/2018



Beiträge des Instituts für Infrastruktur und Ressourcenmanagement
Contributions of the Institute for Infrastructure and Resources Management

Herausgeber:

Prof. Dr. Thomas Bruckner, Prof. Dr. Erik Gawel, Prof. Dr. Robert Holländer und Prof. Dr. Daniela Thrän

Fabian Scheller, Simon Johanning, Thomas Bruckner

IRPsim: A techno-socio-economic energy system model vision for business strategy assessment at municipal level

Beiträge des Instituts für Infrastruktur und Ressourcenmanagement, Universität Leipzig

Herausgegeben von Prof. Dr. Thomas Bruckner, Prof. Dr. Erik Gawel, Prof. Dr. Robert Holländer und
Prof. Dr. Daniela Thrän

Nr. 02/2018

ISSN 2364-4346

<http://www.econstor.eu/escollectionhome/10419/107939>

© Institut für Infrastruktur und Ressourcenmanagement, Universität Leipzig, 2018

Die Schriftenreihe „Beiträge des Instituts für Infrastruktur und Ressourcenmanagement“ erscheint mehrmals im Jahr und stellt in unregelmäßigen Abständen den Forschungsstand unterschiedlicher Themengebiete des Instituts vor. Sie vereint Diskussionsbeiträge, Projekt(teil-)berichte sowie herausragende Abschlussarbeiten. Die Beiträge geben dabei die Meinung der Autoren wieder, nicht notwendigerweise auch die der Herausgeber.

IRPsim: A techno-socio-economic energy system model vision for business strategy assessment at municipal level

Fabian Scheller^{a,*}, Simon Johanning^a, Thomas Bruckner^a

^a*Institute for Infrastructure and Resources Management (IIRM), University Leipzig*

Abstract

Decision makers of municipal energy utilities responsible for future portfolio strategies are confronted with making informed decisions within the scope of continuously evolving systems. To cope with the increasing flexibility of customers, and their autonomous decision-making processes, determining newly established municipal energy-related infrastructure has become a challenge for utilities, which are struggling to develop suitable business models. Even though business portfolio decisions are already supported by energy system models, models only considering rational choices of economical drivers seem to be insufficient. Structural decisions of different market actors are often related to bounded rationality and thus are not fully rational. A combined analysis of sociological and technological dynamics might be necessary to evaluate new business models by providing insights into the interactions between the decision processes of market actors and the performance of the supply system. This research paper outlines a multi-model vision called IRPsim (Integrated Resource Planning and Simulation) including bounded and unbounded rationality modeling approaches. The techno-socio-economic model enables the determining of system impacts of behavior patterns of market actors on the business performance of the energy supply system. The mutual dependencies of the coupled models result in an interactive and dynamic energy model application for multi-year business portfolio assessment. The mixed-integer dynamic techno-economic optimization model IRPopt (Integrated Resource Planning and Optimization) represents an adequate starting point as a result of the novel actor-oriented multi-level framework. For the socio-economic model IRPact (Integrated Resource Planning and Interaction), empirically grounded agent-based modeling turned out to be one of the most promising approaches as it allows for considering various influences on the adoption process on a micro level. Additionally, a large share of available applied research already deals with environmental and energy-related innovations.

Keywords: Techno-socio economic modeling, Bounded and unbounded rationality, Business model assessment, Empirically grounded agent-based modeling of innovation diffusion

1. Introductory remarks

Techno-economic optimization models are one of the main streams in modeling energy systems and supporting informed decision making within the scope of continuously evolving systems. Sophisticated numerical energy system models at the municipal level have to account for the current business portfolio, technological progress, customer behavior, regulatory framework as well as the market environment. However, in a liberalized market, actors along the energy value chain might assess challenges and opportunities from different actor perspectives and apply various criteria, since every single consumer and operator, due to their positioning, contracts, and instruments, has a differing technology-mediated relationship [1]. A successful introduction of innovative business models needs to be accompanied by an appropriate pricing, distribution, and communication strategy [2]. Existing energy system models often neglect the roles different actors play in an existing system architecture [3] and the resulting impact their characteristics, attitude, and behavior might have on the consumer acceptance of specific diffusion processes.

*Corresponding author

Email address: scheller@wifa.uni-leipzig.de (Fabian Scheller)

Thus, to value future strategies that include business model innovations, which might also have an effect on the system infrastructure, it is crucial to account for the technological restrictions of system units. In addition to this, business models should also encompass the dynamics of the market setting by including the commercial processes that arise between multiple market participants in general and in particular those involving customers or more precisely prosumers in order to determine newly established municipal infrastructure. Mental decision structures can be decisive regarding the evaluation and acceptance of an innovation and for any consequences arising from it. A socio-economic bounded rationality approach recognizes that individuals have incomplete knowledge, as well as limited information gathering and processing abilities [4]. Consequently, coupled modeling of technical infrastructure and interacting actors provides decision makers with a supportive analysis of commercial competition and technical counteraction effects for future business models to be investigated [1].

This paper outlines a multi-model vision called *IRPsim* (Integrated Resource Planning and Simulation) of sociological and technological dynamics. A combination of an unbounded rationality model, as well as a bounded rationality model, enables the simulation of feedback effects that decisions of market actors have on the performance of a certain energy supply network as initially described by [5]. In addition to the existing techno-economic modeling approach *IRPopt* (Integrated Resource Planning and Optimization), a socio-economic modeling approach called *IRPact* (Integrated Resource Planning and Interaction) needs to not only consider the heterogeneity of behavioral patterns, but also the communication and interaction structures of market participants [6]. Empirically grounded agent-based modeling turned out to be one of the most promising approaches for socio-economic modeling as it allows for considering various influences on the adoption on a micro level [7]. The multi-model vision is in line with the proposed energy policy roadmap of [1] and the long-term objective of combining the various strands into a single assessment package.

This paper is organized as follows: Section 2 introduces the coupled techno-socio-economic model concept. Section 3 outlines theoretical foundations of the socio-economic modeling domains and introduces the concepts of empirically grounded agent-based modeling of innovation diffusion. Section 4 gives an overview of suggested future work to develop the multi-model vision. Finally, section 5 concludes with a recapitulation.

2. Techno-socio-economic model vision

Future energy-related business portfolio decisions should be supported by energy system models considering the current business portfolio, technological progress, customer behavior, regulatory framework as well as the market environment. The techno-economic mathematical optimization framework *IRPopt* (Integrated Resource Planning and Optimization) [8] supports decision makers of municipal energy utilities regarding future portfolio management. The mathematical optimization model allows for a policy-oriented, technology-based and actor-related assessment of varying energy system conditions in general, and innovative business models in particular. The integrated multi-modal approach is based on a novel six-layer modeling framework built on existing high-resolution modeling building blocks.

The optimization model, which has been implemented in GAMS/CPLEX (General Algebraic Modeling System), allows for solving mixed-integer problems in a quarter-hourly resolution for perennial periods. The major objective is to maximize revenues from different actor perspectives. Thereby, *IRPopt* provides a novel actor-oriented multi-level optimization framework. This is achieved by an explicit modeling of municipal market actors on one layer and state-of-the-art technology processes on another layer as well as resource flow interrelations and service agreements mechanism among and between the different layers. Individual participating market actors and the spatially distributed load, storage and generation technologies are modeled separately. Furthermore, multi-party cooperation is incorporated. Individual actors hold bilateral contracts with each other that handle the business transactions. Due to the chosen approach, decision making of different modeled market actors can be described using the term unbounded rationality [4]. In mathematical programming systems, designers define rules and procedures to engineer outcomes. This falls in line with the statement of [4] that "the operational decisions of local utilities and large independent energy producers are assumed to close to individually fully rational, because of the sophisticated software tools already used to support these decisions. Within the approach presented here, operational decisions, therefore, are made using an optimization model similar to the models applied by utilities." Additionally, due to the novel framework, *IRPopt* permits to determine the optimal operation dispatch and thus the optimal *profitability index* from different market actor perspectives, such as prosumer households, and not only from the municipal utility.

With this in mind, the model-driven decision support system *IRPopt* will be valuable in the context of strategy adjustments and business development processes of utilities. Potential use cases originate from the core business of its

departments, supporting, in particular, the day-to-day business of the strategy and sales unit. Questions the model is particularly suited to address are as follows:

- What effects of customer technology adoption on sales and margins are visible in terms of different scenarios?
- Which company-wide impact of a business model implementation, as well as customer migration flows, can be determined?
- What are optimal community layouts in the context of decentralized autarky system trends and differing municipal conditions?
- What is the value of flexibility regarding balancing and spot markets as well as peak load curtailment for different participating actors?

Initial model applications and business model assessments of *IRPopt* are presented in [9, 10]. The focus has been on decentralized autarky enhancement solutions like self consumption, direct consumption, direct marketing, demand response, net metering and community storage systems.

Scenario and sensitivity analysis is applied to detect the consequences of parameter changes [11]. For this, uncertain environmental conditions, prosumer operations as well as market developments represent a crucial aspect. Since the quality depends on the procedure, a techno-economic multi-method approach seems useful to cover the issues raised. In order to describe the economic boundary conditions, spot market and reserves market prices need to be considered which might be determined or rather projected by employing the optimization model MICOES-Europe (Mixed Integer Cost Optimization of Energy Systems) and the optimization model MICOES-Reserve. While the fundamental model MICOES-Europe uses marginal costs to determine future spot market prices of selected European countries [12], the fundamental model MICOES-Reserve uses opportunity costs to calculate future control power prices [13, 14]. In this context, LICOES-Europe [15] is able to determine the possible future power plant park. Additionally, the investment decision tool MicroGrid [16] might be applied to assess prosumer technology adoption behavior. An overview of the interplay of different optimization models to parameterize *IRPopt* is outlined in Figure 1.

Techno-economic modeling can capture technological interactions, but it cannot endogenize the commercial processes that arise between multiple market participants [1]. "The structural decisions faced by local utilities, independent energy producers, and house owners exhibit increasing levels of ambiguity and mathematical intractability. The orthodox assumptions of unbounded rationality and perfect foresight reduce the set of potential behaviors that require investigation to those that are defined as optimal in some sense. Bounded rationality, on the other hand, introduces the challenge of extracting realistic behavior patterns from an almost unlimited set of possible alternatives." [4]. Different incentives can influence the heterogeneous market actors and might cause a change in their decision behavior in a different way. If certain customers decide to invest in decentralized energy technologies or to shift their load, this might influence the technical infrastructure and the system performance. Additionally, strategies of competitors may also have a relevant effect on the decision behavior of customers. Even if the competitor is not directly influencing the individual actors, their business offers may induce customers to change their provider or make an investment. During the design and implementation of sustainable business portfolios, this can lead to synergy effects or increasing peer pressure, which needs to be subject to closer examination.

In this context, it is important to understand how investment decisions of individual market actors are conducted, since even good innovations might fail or diffuse at a slow rate [18]. For many companies it is hard to predict how business model innovations will diffuse in the dynamic energy-economic environment, resulting in uncertainty about whether an innovation is fit to become a sustainable business model. This may be to a large part because the adoption of these innovations by the intended target groups is not always given, and as [19] shows, doesn't just depend on the qualities of the innovation. Instead, it takes place within a complex social system, in which the diffusion of the respective innovations depends on many factors and mechanisms [20]. Business models and innovations need to encompass the dynamics of the market setting by including the mental decision structures, such as personal characteristics, behavioral attitudes as well as conscious and subconscious purchase decisions, of market participants in general and of customers in particular. As [21] points out, "[...] the diffusion of innovation paradigm postulates that markets are in fact dominated by social influences [...]."

By extending the techno-economic model *IRPopt* with the socio-economic model *IRPact* (Integrated Resource Planning and Interaction), it is possible to consider various energy-economic system drivers as a whole as shown by

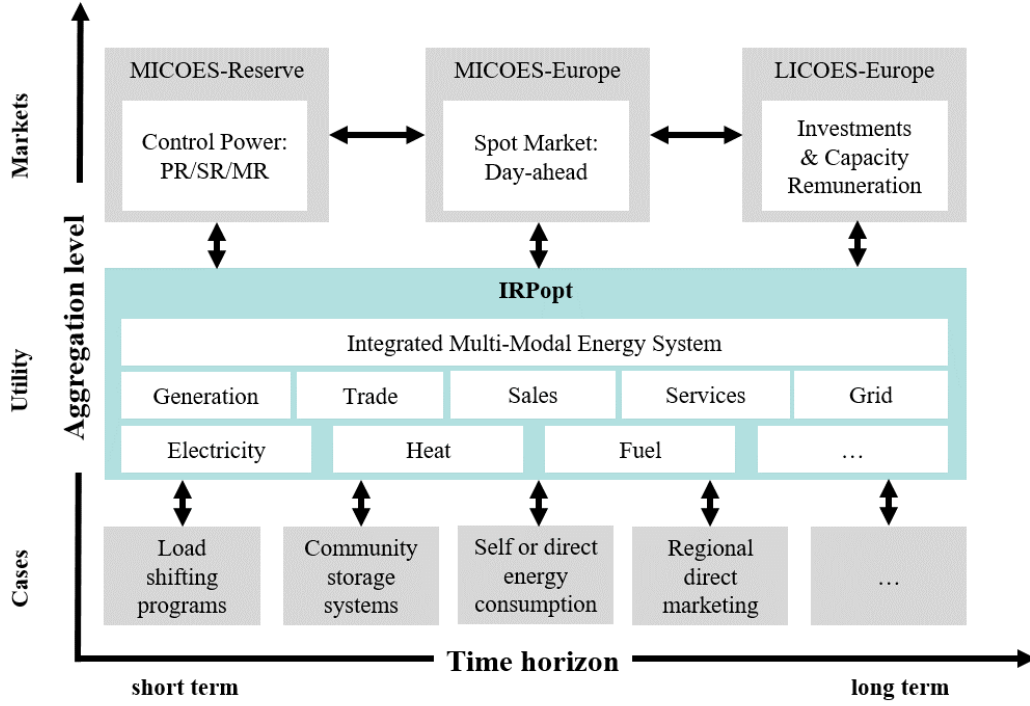


Figure 1: Overview of the interplay of various techno-economic energy system optimization models to parametrize the integrated multi-modal modeling approach IRPopt (MICOES-Reserve [13, 14], MICOES-Europe [12, 14], LICOES-Europe [15], IRPopt [8, 17, 9, 10])

[4, 5]. Socio-economic modeling does not only account for the heterogeneity of bounded-rational mental behavior patterns, which are not only based on economic thinking but also considers the social structures of market actors [6]. This approach makes it possible to simulate acceptance and diffusion of innovations by various customer types and utilities considering different decision-making and network models, as well as the temporal and regional differences in the diffusion process. The simulated *adoption rate* of individual market actors regarding energy-related business models, in turn, directly affects the energy supply network and process technologies of the techno-economic system model *IRPopt*. In contrast, the optimized *profitability index* of individual actors in terms of a given supply network can be considered a single influencing aspect of the decision behavior of the socio-economic system model *IRPact*.

A multi-model system called *IRPsim* (Integrated Resource Planning and Simulation) of an unbounded technical infrastructure optimization and a bounded interacting actors simulation enables the determination of system impacts of socio-economic behavior patterns of market actors on the techno-economic business performance of the energy supply system. A schematic representation of the interplay of the two models is outlined in Figure 2. While *IRPact* includes simulated adoption decisions of the individual market actors (*adoption rate*), *IRPopt* considers the optimized operation dispatch (*profitability index*). This results in an interactive and dynamic energy multi-model application for multi-year business portfolio assessment.

As outlined in Figure 2, *IRPopt* requires parametrization of the system infrastructure. Thereby, market actors and corresponding engineering processes as well as resource flow interrelations and coordination mechanism among and between them need to be defined. Additionally, market principles need to be specified to model realistic issues at the municipal level. Since *IRPact* takes the same market actors into account as *IRPopt*, mental models and social dynamics between them need to be parametrized first. Furthermore, the social network design, as well as the theoretical and empirical grounding, is required for a realistic adoption behavior modeling. While optimization results of a certain system infrastructure provide costs and revenues for each of the participating actors in terms of operational management,

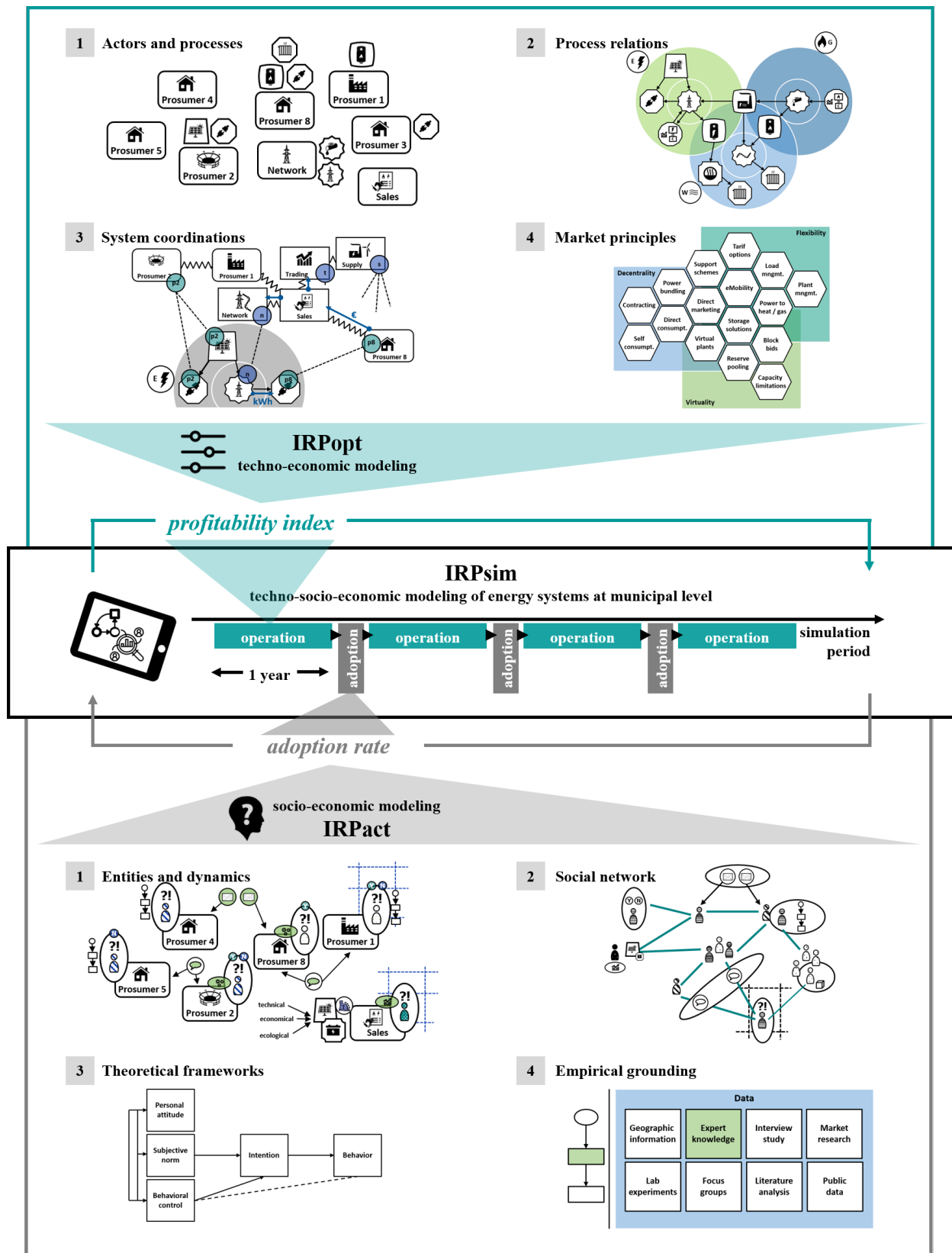


Figure 2: Schematic relation of the energy model vision IRPsim consisting of the techno-economic modeling approach IRPopt and the socio-economic modeling approach IRPact

the simulation results of a certain social system shows the adoption rate for each of the participating actor. This, in turn, affects the system infrastructure and changes the parametrization of *IRPopt*. At the same time, the reevaluated profitability of the adoption decision influences the decision making of the participating actors and thus the adoption process of *IRPact*. The integration layer of *IRPsim* provides the necessary interfaces and mechanisms to enable the information exchange of the multi-model approach and allows to analyze the dependencies of the techno-economic and socio-economic system dynamics. In this sense, a multi-model system of coordinated and matched components as outlined above can demonstrate its great benefits and achievement of robust answers.

From a scientific point of view, the multi-model framework aims to analyze the interrelations between customer behavior and system performance. It can give an answer to the question what synergy and competition effects certain socio-economic customer structures evoke within a techno-economic energy system. The main focus of the research in this context is how and to what extent the adoption behavior of different customer groups regarding innovative business models show competition and counteraction effects on the current and emerging energy supply network. In practice, achieving the vision will provide answer a number of management questions, such as:

- What costs and revenues for market actors occur in terms of business model implementation at the municipal level?
- Which product attributes and market dynamics are necessary for customers to adopt business model innovations?
- What are the interrelations between the innovation diffusion among different customer types and the supply network infrastructure?
- What feedback effects along the value chain of the company and its business units will the innovation initiate?
- Which business model innovations do both have a positive effect on the business performance and are adopted by the customers?

3. Socio-economic modeling approach

Decision makers of municipal energy utilities responsible for product or service innovations are confronted with making informed decisions about complex matters. Insights into the diffusion of innovations can help to detect weak areas in business models and innovation marketing. Particularly quantitative socio-economic models of innovation diffusion analysis that account for the social complexity of the modeled system might assist in the investigation of potential measures and in the development of effective strategies. One promising socio-economic modeling approach for describing diffusion processes is to employ empirically grounded agent-based models [7]. A general overview of the covered research domains and relevant intersections is given in the following.

3.1. Innovation diffusion modeling

Although the roots of innovation diffusion research lie in the late 19th century, studying the diffusion of innovations can generally be traced back to the seminal study of Ryan and Gross in the 1940s in rural sociology about the diffusion of hybrid corn [20, 22]. This might be due to the fact that the "study advanced theoretical exploration of the diffusion process." [22], or because the study "[...] was driven by scholarly interest in the relative influence of economic versus social factors in the adoption of a technological innovation." [22].

A fundamental aspect of innovation diffusion Ryan and Gross identified was the interpersonal communication between farmers. "The hybrid corn study established diffusion as essentially a social process. A farmer typically adopted the innovation because of interpersonal communication with other farmers who already had adopted it [...]" [22]. Through this social process "[...] subjective evaluations of an innovation spread from earlier to later adopters rather than one of rational, economic decision making." [22].

Rogers defines the *diffusion of an innovation* as "[...] the process in which an innovation is communicated through certain channels over time among the members of a social system." [18]. This definition exemplifies the four major elements, namely innovation, communication channels, time, and the social system. Each one of these elements is identifiable in nearly every diffusion research or diffusion campaign [18]. In other words, diffusion can be seen as a "special kind of communication in which the messages are about a new idea. [...] Diffusion is a kind of social change,

defined as the process by which alteration occurs in the structure and function of a social system.” [18]. Thereby, “[a]n *innovation* is an idea, practice or object that is perceived as new by an individual or other unit of adoption.” [18]. The perception of newness matters, but not the absolute newness as described by [23]. “*Adoption* is a decision to make full use of an innovation as the best course of action available. Rejection is a decision not to adopt an innovation.” [18]. The units of adoptions could be individuals, households, institutions or other entities. A summary of operational definitions of presented key concepts is outlined in Table 1.

Table 1: Key concepts of innovation diffusion modeling

Concept	Definition
Product innovation	“Innovation is an idea, practice, or object perceived as new by an individual or other unit of adoption. It can also be an impulse to do something new or bring some social change.” [18]. In this work, a perception of newness matters, but not the absolute newness [23].
Innovation adoption	“Adoption is a decision to make full use of an innovation as the best course of action available. Rejection is a decision not to adopt an innovation.” [18]
Innovation diffusion	Innovation diffusion is “the process by which an innovation is communicated through certain channels over time among the members of a social system.” [18]

Starting from the 1960s, innovation diffusion processes have been investigated using models, which aim at empirical generalizations of prototypical diffusion patterns at *aggregate levels* [21]. As Ryan and Gross stress, social contacts, social interaction and interpersonal communication are important influences on the adoption of new behaviors. Kiesling emphasizes that innovations are not evaluated objectively, but instead, the dynamic formation of attitudes and subjective perceptions are transmitted through communication at *disaggregated levels* [21].

A large amount of *aggregated innovation diffusion models* are refined versions of the Bass model [24], a parsimonious, aggregated innovation diffusion model, based on models of epidemiological spread. The *Bass model* as described in [24] is theoretically based in (epidemiological) contagion models and is based upon the assumption that the timing of initial purchases is related linearly to the number of previous buyers. The goal of the model is to develop a theory of timing of initial purchases for new classes of products. Its key characteristic is that the adoption behavior of imitators is influenced in timing through social pressure. In this context, the following sentence characterizes the theory: “The probability that an initial purchase will be made at T given that no purchase has been made is a linear function of the number of previous buyers.” [24]. Thus, the Bass model intends to formalize literary analysis of Rogers in terms of the the likelihood of the number of purchases $P(T)$ at time T given that no purchase has yet been made. On the one hand, this is dependent on the constant p at $T = 0$ which represents the probability of an initial purchase (coefficient of innovation). On the other hand, the number of purchases is dependent on the product $(\frac{q}{m})$ times $Y(T)$. This product reflects the pressures operating on imitators in terms of an increasing number of previous buyers. Thereby, $(\frac{q}{m})$ represents a scaling constant (where m is the number of total initial purchases and q the coefficient of imitation) and $Y(T)$ represents the number of previous adopters. If $Y(0) = 0$, the constant p and thus the probability of an initial purchase remains. All in all, $P(T)$ can be calculated as follows:

$$P(T) = p + \frac{q}{m}Y(T)$$

From this, Bass [24] derives the sales $S(T)$ at time T as follows:

$$S(T) = P(T)(m - Y(T)) = \left(p + q \int_0^T S(t) \frac{dt}{m}\right) \left(m - \int_0^T S(t) dt\right) = pm + (q - p)Y(T) - \frac{q}{m}(Y(T))^2$$

This adoption behavior exemplifies the exponential growth of initial purchases to a peak, followed by exponential decay. This form shows the aggregated nature of the model, which describes total adoption or rather adoption per time period in a closed form and aggregates the agents into a ‘macro’ variable.

Despite their popularity, these aggregate models have several shortcomings [20, 21]. The most fundamental shortcomings of aggregated innovation diffusion models are their assumption of a homogeneous population. Furthermore, aggregate models cannot differentiate between the social network of one potential adopter and the other, so they have to impose the assumption of a fully connected social network. Additionally, these models require information about events they ought to predict, and lack predictive power.

To overcome these limitations, many approaches employ *disaggregate models*, most notably *agent-based models*. Disaggregated models are models that avoid aggregating model entities individually. They focus on micro behavior instead of macro behavior and are grounded in complexity science. In contrast to macro simulations, where the entire system is described directly and ‘phenomenologically’, societal phenomena of interest are modeled bottom-up based on the underlying processes. The phenomena then emerges from the behavior and micro-level interactions of the agents [21].

3.2. Agent-based modeling

As the name suggests, agent-based models are conceptualized from the perspective of disaggregated units, so-called agents or actors¹, instead of modeling the system on the aggregate level. As noted in [25], no single universally accepted definition of an agent exists. Instead Wooldridge [25] enumerates abilities actor entities need to exhibit in order to be called agents. In their general definition, agents need to exhibit four abilities: autonomy, social ability, reactivity, and pro-activeness. In this, *autonomy* is the ability to act without being directly controlled or manipulated by humans or others, as well as having some control over their actions and internal state. *Social ability* means the use of an agent-communicative language to interact with other agents, where *reactivity* represents the perception of and response to their environment. Finally, *proactiveness* is the ability to take initiative in goal-directed behavior instead of solely responding to stimuli [25]. Most crucially, agent-based models allow for modeling heterogeneity of potential adopters. Since this approach describes actors on the level of their entity, actors can be designed differently from one another. The characterization of agents is proposed which considers interaction between agents but also puts interaction with and immersion in an environment at the heart of the models [26]. A summary of operational definitions of presented key concepts is outlined in Table 2.

Table 2: Key concepts of agent-based modeling

Concept	Definition
Software agent	“An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives.” [25].
Multi-agent model	“A multi-agent system is one that consists of a number of agents, which interact with one another [. . .]. [T]he agents in a multi agent system will be representing or acting on behalf of users or owners with very different goals and motivations.” [27].
Model procedure	Model procedures poses step-wise guidelines for the designing and modeling of complex systems in terms of scientific purposes. This covers activity lists, building blocks, structural items, best practices, design choices, methodological issues as well as functional protocols and frameworks.
Model component	Model components represent the functional elements of complex systems. Master categories are model strategies, model entities and model dynamics [21].

3.3. Empirically grounded modeling

The level of detail with respect to the data and information incorporated into agent-based simulations varies from “Picasso” to “Photograph” models [28]. “An obvious difference relates to the representation of space, ranging from

¹Many publications from the sociological, ecological or socio-economic perspective use the term *agent* to refer to these units, publications in computer science often try to avoid this term, since it might be confused with the concept of software agents, and rather use the term *actor*. In this publication, they will be used interchangeably, and where the distinction between actors and software agents is meaningful, this will be made explicit.

empty and simple artificial landscapes [...] to very detailed, realistic representations of the environment.” [28]. At first, more abstract models (so-called ”Picasso” models) were widely used to show general mechanisms rather than to make exact predictions. Since *IRPact* aims to predict innovation diffusion processes, the following research needs to focus on detailed models (so-called ”Photograph” models).

In this context, different aspects as actor heterogeneity can enter agent-based innovation diffusion models through different values of characteristics such as income or preference [28], various sources of knowledge [29], different types of agents that differ in decision rules and interaction with other agents and the environment [28]. This is due to the fact that the behavior of the modeled agents ”[...] can be empirically informed using a combination of different kinds of data (e.g. qualitative and quantitative) and data collection methods [...] that support multiple approaches to represent actor decision making in an agent (e.g., heuristic decision trees, utility functions).” [26]. Through this they ”[...] can go beyond the typical representation of a population or average individual in EBM [equation based models] and capture the heterogeneity of individual actors, their characteristics, and decision-making structures.” [26]. Thus, empirically grounded agent-based models of innovation diffusion can reproduce and explain complex non-linear diffusion patterns observed in the real world as a result of simple local micro-level interactions [21]. A summary of operational definitions of presented key concepts is outlined in Table 3.

Table 3: Key concepts of empirically grounded modeling

Concept	Definition
Grounded theory	Grounded theory is defined as “discovery of theory from data systematically obtained from social research.” [30]. The derived constructs constitute the grounding of the models. In this work, it refers to theoretical grounding as well as empirical grounding.
Theoretical grounding	Theoretical grounding describes the characterization of the model. It “aims at surfacing the intended model as an artifact: qualifying its contours and interfaces.” [31].
Empirical grounding	Empirical grounding describes the parametrization of the model. It “aims at connecting model and target system, through giving values to the set of parameters in order to enable simulation.” [31].
Micro-level approach	Micro-level approach describes a “bottom-up” or “microscopic” modeling [6]. “Rather than describing the whole system directly and phenomenologically, macro-scale dynamics in [system models] are emergent phenomena that arise from micro-level interactions between agents when the model is executed.” [7].
Case-based applications	Case-based applications “have an empirical space-time circumscribed target domain. [...] The goal [...] is to find a micro-macro generative mechanism that can allow the specificity of the case [...]. [32]. They are usually built “to provide forecasts, decision support, and policy analysis [...]” [7].

3.4. Empirically grounded agent-based case studies

Given the advantages, the described models are losing their niche character and gaining importance as a valuable methodology for describing diffusion processes [7]. Since empirically grounded agent-based models are foremost applied to reflect real market issues, papers with real-world case studies to support decision makers are increasing [33]. Case-based applications “have an empirical space-time circumscribed target domain.” [32]. They are usually built “to provide forecasts, decision support, and policy analysis [...]” [7]. In this context, the application domain of empirically grounded agent-based models of innovation diffusion is very versatile. With respect to various relevant research papers, the approach has been applied to the following major substantive domains: mobility and logistics, consumption and retail, energy and utilities, nature and environment as well as public and education. An overview of reviewed and classified papers is given in Table 4.

Table 4: Identified application domains of empirically grounded agent-based models

Domain	Example	Source
Mobility and logistics	[34] “introduce an empirically grounded, spatially explicit, agent-based model, InnoMind (Innovation diffusion driven by changing MINDs), to simulate the effects of policy interventions and social influence on consumers’ transport mode preferences.”	[35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [2], [34]
Consumption and retail	[45] aim “to gain insights on how social influences can affect the market inequalities in the motion picture market.”	[46], [47], [48], [45], [49], [50], [51], [52]
Energy and utilities	[53] “propose an agent-based model to simulate how changes to the Italian support scheme will affect the diffusion of PV [photovoltaic] systems among single- or two-family homes.”	[54], [37], [55], [56], [57], [58], [59], [53]
Nature and environment	[56] “develop an agent-based simulation model linked to Geographic Information System (GIS) data in order to investigate the spatial–temporal diffusion of agricultural biogas plants, given constraints on the local availability of feed-stock resources.”	[60], [61], [62], [63], [64], [65], [66], [67]
Public and education	[28] apply “a data-driven case study [...] of residential mobility [in a medium-sized town in Germany] to systematically explore the role of model detail on model performance.”	[68], [69], [70], [71], [72], [28]

It is obvious that a large share of the surveyed research papers deal with environmental and energy-related innovations. Product innovations are analyzed ranging from hybrid or electric cars [34, 36, 40, 38] to biofuels [2] and photovoltaic panels [59]. Moreover, smart meter diffusions have also been analyzed [37]. One reason might be the high societal relevance of these innovations. Promoting consumer choices with respect to environmental technologies is crucial to meet the challenge of climate change and its associated impacts since the adoption of such environmental-friendly products generally only occurs slowly [36]. This also falls in line with the statement of [34] that environmentally-friendly technologies require influencing the demand side to diffuse on a larger scale. Another reason is the need for an individually-based modeling approach. They claim that “the key strength of agent-based-models is that they overcome the homogeneity assumption of traditional aggregate diffusion models.” [7]. Environmental innovations oftentimes polarize and divide consumers between proponents and opponents. To overcome this homogeneity assumption, agent-based models seem to be appropriate in environmental and energy-related innovations. Because of this, basing *IRPact* on empirically grounded agent-based models seems to be the natural choice due to the focus of *IRPsim* on energy and environmental assessments.

4. Future research

In view of the key question *how energy utilities can and need to shape their business portfolio to manage and survive in a highly dynamic environment*, the system model vision *IRPsim* aims to provide managers with a multi-model decision support system for innovative business model assessments of differing system conditions of interest like business portfolio, legal framework as well as customer behavior and market environment. The model environment intends to match highly stylized modeling for theoretical inquiries as well as highly specific modeling for practical applications.

In this context, *IRPact* aims to investigate the level of adoption of business model innovations and detect success factors by including mental and social dynamics. The development of a case-based empirically grounded agent-based

model allows for depicting the heterogeneous agents and social dynamics and to examine their interactions in various scenarios. While *IRPopt* is already in a mature state, the focus of the research needs to be on designing and developing *IRPact* in order to achieve the outlined multi-model vision. For this, the following objectives need to be addressed:

- *Examine and determine the innovation environment and the agent structure:* Examine and structure the market, products, and actors and identify the main characteristics of the environment and the innovation chosen.
- *Analyze and characterize the behavior of agents:* Theoretical and empirical analysis of the mental and social dynamics in terms of the factors that drive adoption and diffusion of innovations by households and business enterprises.
- *Model and implement the recursive socio-economic simulation software as „experimental lab“:* Model and implement the multi-agent model based on interacting agents with mental decision structures, social dynamics and respective environmental influences.
- *Integrate the socio- and techno-economic energy system model approach:* Determine interfaces and combine the techno-economic model with the socio-economic model using a technical integration layer.
- *Identify innovative business models and derive implications for business units:* Simulate and evaluate market scenarios using an agent- and optimization-based modeling approach and derive suggestions.

5. Concluding remarks

Business portfolio decisions should be supported by energy system models considering the current business portfolio, the customer base, the regulatory framework as well as the market environment. The combination of sociological and technological dynamics within the energy system simulation *IRPsim* might provide some unique benefits for both theory and practice. In addition to the existing techno-economic modeling approach *IRPopt*, a socio-economic modeling approach called *IRPact* would not only consider the heterogeneity of behavioral patterns but also the communication and interaction structures of market participants [6]. An empirically grounded agent-based model makes it possible to simulate acceptance and diffusion of innovations by various customer types and municipal utilities considering different decision-making and network models, considering the temporal and regional differences in the diffusion process [21].

The presented combination of the multi-model approach enables the simulation of feedback effects that decisions of market actors have on the performance of a certain energy supply network [5]. Thus, the realization of the suggested research roadmap might further yield insights into how policy measures are applied regarding different techno-economic and socio-economic structures of municipalities. In this context, the development process of *IRPact* should be guided by a number of existing case-based models. Before and after coupling, the models ought to be applied to real-world scenarios at the municipal level in order to provide decision support.

References

- [1] T. Bruckner, R. Morrison, T. Wittmann, Public policy modeling of distributed energy technologies: strategies, attributes, and challenges, *Ecological Economics* 54 (2) (2005) 328–345. doi:10.1016/j.ecolecon.2004.12.032.
- [2] C. Stummer, E. Kiesling, M. Günther, R. Vetschera, Innovation diffusion of repeat purchase products in a competitive market: An agent-based simulation approach, *European Journal of Operational Research* 245 (1) (2015) 157–167. doi:10.1016/j.ejor.2015.03.008.
- [3] B. P. Koirala, E. Koliou, J. Friege, R. A. Hakvoort, P. M. Herder, Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems, *Renewable and Sustainable Energy Reviews* 56 (2016) 722–744. doi:10.1016/j.rser.2015.11.080.
- [4] T. Wittmann, T. Bruckner, Agent-based modeling of urban energy supply systems facing climate protection constraints, in: *Fifth Urban Research Symposium*, 2009.
- [5] T. Wittmann, T. Bruckner, Agentenbasierte modellierung urbaner energiesysteme, *Wirtschaftsinformatik* 49 (5) (2007) 352–360.
- [6] E. Bonabeau, Agent-based modeling: Methods and techniques for simulating human systems, *Proceedings of the National Academy of Sciences of the United States of America* 99 (Suppl 3) (2002) 7280–7287. doi:10.1073/pnas.082080899.
- [7] E. Kiesling, M. Günther, C. Stummer, L. M. Wakolbinger, Agent-based simulation of innovation diffusion: a review, *Central European Journal of Operations Research* 20 (2) (2012) 183–230. doi:10.1007/s10100-011-0210-y.

- [8] F. Scheller, B. Burgenmeister, H. Kondziella, S. Kühne, D. G. Reichelt, T. Bruckner, Towards integrated multi-modal municipal energy systems: An actor-oriented optimization approach, *Applied Energy* 228 (2018) 2009–2023. doi:10.1016/j.apenergy.2018.07.027.
- [9] F. Scheller, D. G. Reichelt, S. Dienst, S. Johanning, S. Reichardt, T. Bruckner, Effects of implementing decentralized business models at a neighborhood energy system level: A model based cross-sectoral analysis, in: 14th International Conference on the European Energy Market (EEM), Dresden, 2017, pp. 1–6. doi:10.1109/EEM.2017.7981910.
- [10] F. Scheller, S. Johanning, D. G. Reichelt, S. Reichardt, T. Bruckner, Competition effects of simultaneous application of flexibility options within an energy community, in: 15th International Conference on the European Energy Market (EEM), Lodz, 2018, pp. 1–5. doi:10.1109/EEM.2018.8470007.
- [11] T. Bruckner, Dynamische Energie- und Emissionsoptimierung regionaler Energiesysteme, Dissertation. Universität Würzburg, 1996.
- [12] D. Böttger, M. Götz, M. Theofilidi, T. Bruckner, Control power provision with power-to-heat plants in systems with high shares of renewable energy sources—An illustrative analysis for Germany based on the use of electric boilers in district heating grids, *Energy* 82 (2015) 157–167. doi:10.1016/j.energy.2015.01.022.
- [13] D. Böttger, T. Bruckner, Market design improvements in the German balancing power market—A fundamental model analysis, in: 10th Conference on Energy Economics and Technology “Sustainable Energy Security”, Dresden, 2015.
- [14] D. Böttger, Energiewirtschaftliche Auswirkungen der Power-to-Heat-Technologie in der Fernwärmeversorgung bei Vermarktung am Day-ahead Spotmarkt und am Regelleistungsmarkt, Dissertation, Universität Leipzig (2017).
- [15] M. Götz, Ökonomische Effekte durch die Einführung von Kapazitätsmechanismen im deutschen und europäischen Strommarkt, Dissertation, Universität Leipzig (2018).
- [16] T. Beck, H. Kondziella, G. Huard, T. Bruckner, Optimal operation, configuration and sizing of generation and storage technologies for residential heat pump systems in the spotlight of self-consumption of photovoltaic electricity, *Applied Energy* 188 (2017) 604–619. doi:10.1016/j.apenergy.2016.12.041.
- [17] F. Scheller, J. Krone, S. Kühne, T. Bruckner, Provoking Residential Demand Response Through Variable Electricity Tariffs - A Model-Based Assessment for Municipal Energy Utilities, Technology and Economics of Smart Grids and Sustainable Energy 3 (1) (2018) 7. doi:10.1007/s40866-018-0045-x.
- [18] E. M. Rogers, Diffusion of innovations, 5th Edition, Free Press, New York, 2003.
- [19] E. R. Frederiks, K. Stenner, E. V. Hobman, Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour, *Renewable and Sustainable Energy Reviews* 41 (2015) 1385–1394. doi:10.1016/j.rser.2014.09.026.
- [20] N. Schwarz, Umweltinnovationen und Lebensstile: Eine raumbezogene, empirisch fundierte Multi-Agenten-Simulation, Vol. 3, Metropolis-Verlag GmbH, 2007.
- [21] E. Kiesling, Planning the market introduction of new products: An agent-based simulation of innovation diffusion, Wien, 2011. URL <http://othes.univie.ac.at/16743/UBWVolltextamHochschulschriftenserverderUBWien>
- [22] T. W. Valente, E. M. Rogers, The origins and development of the diffusion of innovations paradigm as an example of scientific growth, *Science Communication* 16 (3) (2016) 242–273. doi:10.1177/1075547095016003002.
- [23] K. Lyytinen, G. M. Rose, The disruptive nature of information technology innovations: the case of internet computing in systems development organizations, *MIS quarterly* (2003) 557–596.
- [24] F. M. Bass, A new product growth for model consumer durables, *Management Science* 15 (5) (1969) 215–227. doi:10.1287/mnsc.15.5.215.
- [25] M. J. Wooldridge, Agent technology: foundations, applications, and markets, Springer Science & Business Media, 1998. doi:10.1007/978-3-662-03678-5.
- [26] A. R. Bell, D. T. Robinson, A. Malik, S. Dewal, Modular abm development for improved dissemination and training, *Environmental Modelling & Software* 73 (2015) 189–200. doi:10.1016/j.envsoft.2015.07.016.
- [27] M. Wooldridge, An introduction to multiagent systems, John Wiley & Sons, 2009.
- [28] C. M. Buchmann, K. Grossmann, N. Schwarz, How agent heterogeneity, model structure and input data determine the performance of an empirical ABM – A real-world case study on residential mobility, *Environmental Modelling & Software* 75 (2016) 77–93. doi:10.1016/j.envsoft.2015.10.005.
- [29] A. Smajgl, O. Barreteau, Framing options for characterising and parameterising human agents in empirical abm, *Environmental Modelling & Software* 93 (2017) 29–41. doi:10.1016/j.envsoft.2017.02.011.
- [30] B. G. Glaser, A. L. Strauss, The discovery of grounded theory, Chicago (US): Aldine.
- [31] A. Smajgl, O. Barreteau (Eds.), Empirical Agent-Based Modelling - Challenges and Solutions, Springer New York, New York, NY, 2014. doi:10.1007/978-1-4614-6134-0.
- [32] R. Boero, F. Squazzoni, Does empirical embeddedness matter? Methodological issues on agent-based models for analytical social science, *Journal of Artificial Societies and Social Simulation* 8 (4).
- [33] A. Smajgl, O. Barreteau, Series foreword, in: A. Smajgl, O. Barreteau (Eds.), Empirical Agent-Based Modelling - Challenges and Solutions, Springer New York, New York, NY, 2014, pp. v–viii. doi:10.1007/978-1-4614-6134-0.
- [34] I. Wolf, T. Schröder, J. Neumann, G. de Haan, Changing minds about electric cars: An empirically grounded agent-based modeling approach, *Technological Forecasting and Social Change* 94 (2015) 269–285. doi:10.1016/j.techfore.2014.10.010.
- [35] O. van Vliet, B. d. Vries, A. Faaij, W. Turkenburg, W. Jäger, Multi-agent simulation of adoption of alternative fuels, *Transportation Research Part D: Transport and Environment* 15 (6) (2010) 326–342. doi:10.1016/j.trd.2010.03.006.
- [36] M. J. Eppstein, D. K. Grover, J. S. Marshall, D. M. Rizzo, An agent-based model to study market penetration of plug-in hybrid electric vehicles, *Energy Policy* 39 (6) (2011) 3789–3802. doi:10.1016/j.enpol.2011.04.007.
- [37] T. Zhang, W. J. Nuttall, Evaluating Government’s Policies on Promoting Smart Metering Diffusion in Retail Electricity Markets via Agent-Based Simulation*, *Journal of Product Innovation Management* 28 (2) (2011) 169–186. doi:10.1111/j.1540-5885.2011.00790.x.
- [38] E. Shafiei, H. Thorkelsson, E. I. Ásgeirsson, B. Davidsdottir, M. Raberto, H. Stefansson, An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland, *Technological Forecasting and Social Change* 79 (9) (2012) 1638–1653. doi:10.1016/j.techfore.2012.05.011.

- [39] M. Tran, Agent-behaviour and network influence on energy innovation diffusion, *Communications in Nonlinear Science and Numerical Simulation* 17 (9) (2012) 3682–3695. doi:10.1016/j.cnsns.2012.01.016.
- [40] M. Brown, Catching the PHEVer: Simulating Electric Vehicle Diffusion with an Agent-Based Mixed Logit Model of Vehicle Choice, *Journal of Artificial Societies and Social Simulation* 16 (2). doi:10.18564/jasss.2127.
- [41] P. Plötz, T. Gnann, M. Wietschel, Modelling market diffusion of electric vehicles with real world driving data — Part I: Model structure and validation, *Ecological Economics* 107 (2014) 411–421. doi:10.1016/j.ecolecon.2014.09.021.
- [42] D. McCoy, S. Lyons, Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland, *Energy Research & Social Science* 3 (2014) 89–101. doi:10.1016/j.erss.2014.07.008.
- [43] D. Natalini, G. Bravo, Encouraging Sustainable Transport Choices in American Households: Results from an Empirically Grounded Agent-Based Model, *Sustainability* 6 (1) (2013) 50–69. doi:10.3390/su6010050.
- [44] T. Gnann, P. Plötz, A. Kühn, M. Wietschel, Modelling market diffusion of electric vehicles with real world driving data—German market and policy options, *Transportation Research Part A: Policy and Practice* 77 (2015) 95–112.
- [45] T. L. J. Broekhuizen, S. A. Delre, A. Torres, Simulating the Cinema Market: How Cross-Cultural Differences in Social Influence Explain Box Office Distributions, *Journal of Product Innovation Management* 28 (2) (2011) 204–217. doi:10.1111/j.1540-5885.2011.00792.x.
- [46] S. A. Delre, W. Jager, T. Bijmolt, M. A. Janssen, Targeting and timing promotional activities: An agent-based model for the takeoff of new products, *Journal of Business Research* 60 (8) (2007) 826–835. doi:10.1016/j.jbusres.2007.02.002.
- [47] S. Cantono, G. Silverberg, A percolation model of eco-innovation diffusion: The relationship between diffusion, learning economies and subsidies, *Technological Forecasting and Social Change* 76 (4) (2009) 487–496. doi:10.1016/j.techfore.2008.04.010.
- [48] M. E. Schramm, K. J. Trainor, M. Shanker, M. Y. Hu, An agent-based diffusion model with consumer and brand agents, *Decision Support Systems* 50 (1) (2010) 234–242. doi:10.1016/j.dss.2010.08.004.
- [49] P. S. van Eck, W. Jager, P. S. H. Leeftang, Opinion leaders' role in innovation diffusion: A simulation study, *Journal of Product Innovation Management* 28 (2) (2011) 187–203. doi:10.1111/j.1540-5885.2011.00791.x.
- [50] C. Swinerd, K. R. McNaught, Simulating the diffusion of technological innovation with an integrated hybrid agent-based system dynamics model, *Journal of simulation* 8 (3) (2014) 231–240. doi:10.1057/jos.2014.2.
- [51] G. Jiang, P. R. Tadikamalla, J. Shang, L. Zhao, Impacts of knowledge on online brand success: An agent-based model for online market share enhancement, *European Journal of Operational Research* 248 (3) (2016) 1093–1103. doi:10.1016/j.ejor.2015.07.051.
- [52] Y. Xiao, J. Han, Forecasting new product diffusion with agent-based models, *Technological Forecasting and Social Change* 105 (2016) 167–178. doi:10.1016/j.techfore.2016.01.019.
- [53] J. Palmer, G. Sorda, R. Madlener, Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation, *Technological Forecasting and Social Change* 99 (2015) 106–131. doi:10.1016/j.techfore.2015.06.011.
- [54] J. Zhao, E. Mazhari, N. Celik, Y.-J. Son, Hybrid agent-based simulation for policy evaluation of solar power generation systems, *Simulation Modelling Practice and Theory* 19 (10) (2011) 2189–2205. doi:10.1016/j.simpat.2011.07.005.
- [55] B. M. Sopha, C. A. Klöckner, E. G. Hertwich, Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation, *Energy Policy* 39 (5) (2011) 2722–2729.
- [56] G. Sorda, Y. Sunak, R. Madlener, An agent-based spatial simulation to evaluate the promotion of electricity from agricultural biogas plants in Germany, *Ecological Economics* 89 (2013) 43–60. doi:10.1016/j.ecolecon.2013.01.022.
- [57] T. Murakami, Agent-based simulations of the influence of social policy and neighboring communication on the adoption of grid-connected photovoltaics, *Energy Conversion and Management* 80 (2014) 158–164. doi:10.1016/j.enconman.2014.01.033.
- [58] A. Kowalska-Pyzalska, K. Maciejowska, K. Suszczyński, K. Sznajd-Weron, R. Weron, Turning green: Agent-based modeling of the adoption of dynamic electricity tariffs, *Energy Policy* 72 (2014) 164–174. doi:10.1016/j.enpol.2014.04.021.
- [59] V. Rai, S. A. Robinson, Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors, *Environmental Modelling & Software* 70 (2015) 163–177. doi:10.1016/j.envsoft.2015.04.014.
- [60] R. Barthel, S. Janisch, N. Schwarz, A. Trifkovic, D. Nickel, C. Schulz, W. Mauser, An integrated modelling framework for simulating regional-scale actor responses to global change in the water domain, *Environmental Modelling & Software* 23 (9) (2008) 1095–1121. doi:10.1016/j.envsoft.2008.02.004.
- [61] H.-J. Mosler, T. Martens, Designing environmental campaigns by using agent-based simulations: strategies for changing environmental attitudes, *Journal of environmental management* 88 (4) (2008) 805–816. doi:10.1016/j.jenvman.2007.04.013.
- [62] N. Schwarz, A. Ernst, Agent-based modeling of the diffusion of environmental innovations — An empirical approach, *Technological Forecasting and Social Change* 76 (4) (2009) 497–511. doi:10.1016/j.techfore.2008.03.024.
- [63] P. Windrum, T. Ciarli, C. Birchenhall, Consumer heterogeneity and the development of environmentally friendly technologies, *Technological Forecasting and Social Change* 76 (4) (2009) 533–551. doi:10.1016/j.techfore.2008.04.011.
- [64] G. Bravo, E. Vallino, A. K. Cerutti, M. B. Pairotti, Alternative scenarios of green consumption in Italy: An empirically grounded model, *Environmental Modelling & Software* 47 (2013) 225–234.
- [65] S. Balbi, C. Giupponi, P. Perez, M. Alberti, A spatial agent-based model for assessing strategies of adaptation to climate and tourism demand changes in an alpine tourism destination, *Environmental Modelling & Software* 45 (2013) 29–51. doi:10.1016/j.envsoft.2012.10.004.
- [66] O. Barreteau, E. Sauquet, J. Riaux, N. Gailliard, R. Barbier, Agent based simulation of drought management in practice, in: *Advances in social simulation*, Springer, 2014, pp. 237–248. doi:10.1007/978-3-642-39829-2_21.
- [67] T. Jensen, G. Holtz, E. J. Chappin, Agent-based assessment framework for behavior-changing feedback devices: Spreading of devices and heating behavior, *Technological Forecasting and Social Change* 98 (2015) 105–119. doi:10.1016/j.techfore.2015.06.006.
- [68] A. G. Dunn, B. Gallego, Diffusion of Competing Innovations: The Effects of Network Structure on the Provision of Healthcare, *Journal of Artificial Societies and Social Simulation* 13 (4). doi:10.18564/jasss.1690.
- [69] P. Ahrweiler, A. Pyka, N. Gilbert, A New Model for University–Industry Links in Knowledge–Based Economies*, *Journal of Product Innovation Management* 28 (2) (2011) 218–235. doi:10.1111/j.1540-5885.2010.00793.x.
- [70] E. J. Chappin, M. R. Afman, An agent-based model of transitions in consumer lighting: Policy impacts from the E.U. phase-out of incandescents, *Environmental Innovation and Societal Transitions* 7 (2013) 16–36. doi:10.1016/j.eist.2012.11.005.

- [71] V. Gaube, A. Remesch, Impact of urban planning on household's residential decisions: An agent-based simulation model for Vienna, *Environmental Modelling & Software* 45 (2013) 92–103. doi:10.1016/j.envsoft.2012.11.012.
- [72] A. Smajgl, E. Bohensky, Behaviour and space in agent-based modelling: Poverty patterns in East Kalimantan, Indonesia, *Environmental Modelling & Software* 45 (2013) 8–14. doi:10.1016/j.envsoft.2011.10.014.