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An agent-based simulation approach for the new product diffusion of a novel biomass fuel

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Abstract. Marketing activities support the market introduction of innovative goods or services by furthering their diffusion and, thus, their success. However, such activities are rather expensive. Managers must therefore decide which specific marketing activities to apply to which extent and/or to which target group at which point in time. In this paper we introduce an agent-based simulation approach that supports decision makers in these concerns. The practical applicability of our tool is illustrated by means of a case study of a novel, biomass-based fuel that will likely be introduced on the Austrian market within the next five years.

Keywords: agent-based simulation; diffusion of innovation; marketing; biomass fuel

1 Introduction

Innovations have become an indispensable factor for securing the long-term success of enterprises (Tseng, 2008). As comparatively few new products succeed on the market (Stevens and Burley, 1997), market introduction involves considerable economic risks that can be reduced by applying marketing activities in the right manner (e.g., to the right extent, the right target group and/or at the right point(s) in time). Accordingly, a vast body of literature on new product diffusion has been published, with the diffusion model introduced by Bass (1969) being the most popular (Fildes *et al*, 2008). The Bass model provides a closed formula describing the aggregated effects of (external) mass communication and (internal) word-of-mouth communication on the diffusion process. It has later on been extended by other authors to include additional influential factors such as price, differentiated forms of advertising or specific market characteristics (e.g., Robinson

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and Lakhani, 1975; Mahajan *et al*, 1990; Parker, 1994) and serves as basis for several simulation models of new product diffusion (e.g., Howick and Whalley, 2008). However, these models do not distinguish between individual characteristics of consumers, thus neglecting their heterogeneity in preferences and behaviour.

In addressing this shortcoming, we have developed an agent-based simulation approach that supports managers in analysing the influence that various marketing activities and policies have on the adoption behaviour of consumers who have individual preferences and are embedded in a social network. To the end of illustrating the practicability of our approach, we provide a sample application referring to a novel biomass fuel where our computer simulation particularly allows configuring marketing activities with respect to timing (e.g., continuous vs. intermittent), targeting (e.g., consumers' roles in the social network or geographical position) and/or pricing.

The remainder of this paper is structured as follows: First, we provide some background information on agent-based modelling in the context of diffusion research and outline the contributions of our work. After a brief description of the new biomass fuel that serves as an application case, we introduce our agent-based simulation approach. Next, results from four sets of simulation runs are discussed. Finally, we summarise key findings and provide suggestions for further research.

2 Background

Traditional analytical models of innovation diffusion are limited in their ability to capture the full complexity of this process and, thus, simulation approaches have received growing attention in scientific literature. They can be designed for different levels of abstraction, ranging from macro-level to micro-level perspectives (for a discussion see Borshchev and Fillipov, 2004, or Davis *et al*, 2007). System dynamics modelling, for instance, is a typical macro-level approach. For applications in the domain of innovation diffusion research see the works of Homer (1987) or Maier (1998). Agent-based simulation, on the other hand, constitutes a prime example for a micro-level approach. It handles independent entities (e.g., consumers) and, thus, meets the need to address their actions (e.g., purchases) at a considerably more individualised level (Baxter *et al*, 2003). While agents decide on the basis of limited (local) information, observing their individual (e.g., adoption) choices allows for analysing the resulting emergent behaviour (e.g., diffusion patterns) at the macroscopic level (also cf. McFadden, 1974; Mahajan *et al*, 1990; Bonabeau, 2002). Due to this bottom-up process an agent-based simulation is particularly suitable when representing interactions between consumers such as communication within a social network (Macy and Willer, 2002). Thus, such approaches allow capturing complex structures and dynamics without knowing the exact global interdependencies (Borshchev and Fillipov, 2004).

In the field of innovation diffusion research, most studies applying an agent-based simulation approach have either focused on the structure of the social network that determines the interactions between agents (e.g., Alkemade and Castaldi, 2005; Deffuant *et al*, 2005; Delre *et al*, 2007b) or have simulated the interplay between producers and consumers by incorporating product characteristics and modifiable product designs in the respective models (e.g., Janssen and Jager, 2002; Ma and Nakamori, 2005). Only few works have used an agent-based approach to investigate the impact of different marketing strategies on the diffusion process (e.g., Delre *et al*, 2007a; Jager, 2007).

With respect to these predecessors, our contribution to the field is sixfold: Firstly, in designing our agents we take into account such characteristics as consumer type (e.g., price-sensitive consumers), geographical position, and role in the social network (e.g., expert, opinion leader). Secondly, we explicitly define product attributes such as price, product quality, and environmental friendliness. Thirdly, we integrate the concept of innovativeness (cf. Rogers, 2003) by allowing for individualised adoption behaviour of agents. Fourthly, the model permits the simulation of different marketing activities and strategies that may be designed with respect to the agents' characteristics. Fifthly, we not only model adoption behaviour, but also take into account repurchases. Finally, we focus on a real-world innovation, i.e., a novel (second-generation) fuel from biomass that is potentially of high practical relevance for future developments on the fuel market.

3 Case study

The above mentioned application case deals with an innovative fuel from biomass called BioFiT (an acronym that refers to the raw material biomass and the underlying chemical process, namely the Fischer-Tropsch synthesis) that is under development at the Vienna University of Technology, Institute of Chemical Engineering. Note that the conversion of biomass (i.e., biodegradable products and wastes in agriculture, industry, or households) into high-quality liquid transportation fuels by thermochemical processes (biomass-to-liquids, BTL) may contribute to overcome the difficulties associated with conventional (fossil) fuels with respect to, e.g., CO_2 emissions, comparatively high volatility of price, and security of energy supplies. While synthetic fuels from biomass are not available on the market yet, BioFiT or other BTL fuels could be ready for market introduction in roughly three to five years.

Compared to currently available (non-BTL) biofuels, BioFiT offers several advantages. While conventional biofuels depend on a narrow range of raw materials, such as wheat or corn for bioethanol, or rapeseed for biodiesel, BioFiT can be produced from various types of biomass. In addition, other biofuels necessitate significant changes in the transport sector, both in terms of vehicle engines and distribution channels, whereas BioFiT is fully compatible with the existing infrastructure, and thus eliminates important technical barriers to its adoption (Fürnsinn, 2007). In addition, BioFiT provides superior combustion properties, extremely low sulphur-contents and unlimited miscibility with conventional fuels, leading to enhanced engine performance and lower emissions while, in contrast, currently available first-generation biodiesel products (RME, FAME) have had issues with damaged seals or fuel pipes and have made the installation of special materials necessary (Kilcarr, 2006).

4 Agent-based simulation approach

In our agent-based simulation, we consider N consumer agents who are embedded in a social network. For T simulation periods they are either idle, communicate which each other (i.e., exchange information on BioFiT) and/or purchase BioFiT or a fossil fuel, respectively. Their purchasing decisions are influenced through a set of marketing activities that, for instance, have an impact on some consumers' knowledge about the product or alter the product price. In the remainder of this section, we describe how consumer agents, the social network, information transfer, purchasing process, and marketing activities have been modelled. An overview of how these entities are interrelated is provided in Figure 1.

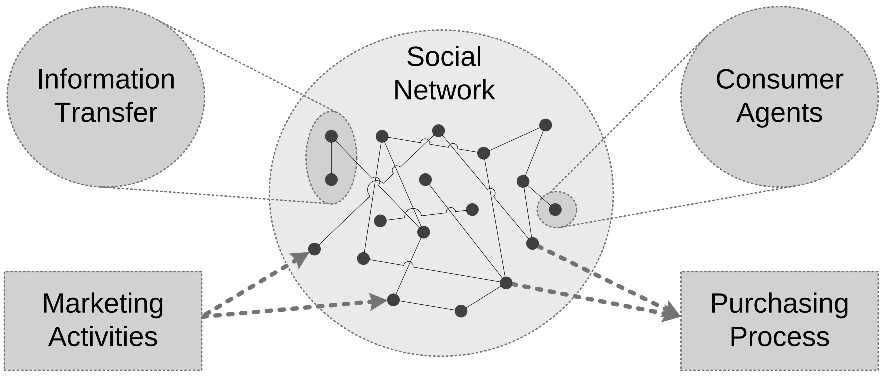

Figure 1: Overview of simulation entities.

4.1 Consumer agents

Each consumer agent i $(i = 1, \dots, N)$ is featured with individual preferences, a geographical position, a tanking behaviour, a (variable) level of information about the product and an influence level all of which are described in the following.

Agents have preferences $w_{i,k}$ for K specific product attributes k $(k = 1, \dots, K)$. In our application we consider the attributes price, quality and expected environmental friendliness. During initialisation the agents' individual preferences are set according to one of four basic consumer types. Accordingly, market may be roughly divided in four segments. Price-sensitive consumers form the largest market segment. They do not attach much importance to product quality, but place great emphasis on low prices. Quality-seeking consumers from the second segment choose high-quality products for purchase. Therefore, we introduce a variable $ppq_{i,t}$ that stands for the perceived product quality $(0 \leq ppq_{i,t} \leq 1)$ of agent i in simulation period t $(t = 1, \dots, T)$. Starting from an initial value, the perceived product quality approaches the "true value" when the customer learns more about it with each purchase (see Eq. (4) below for a formal description). A third consumer segment comprises environmentally conscious consumers ("eco-consumers") who are strongly guided by a product's green image whereas price or quality are less important. The smallest segment consists of the so-called "snob buyers" modelled as consumers who want to use exclusive products and/or account price as a proxy for quality (cf. Leibenstein, 1950).

In order to set the agents' geographical positions $pos_i = (posx_i, posy_i)$, we mapped the distribution of the Austrian population on a virtual landscape with some areas of high population density (i.e., cities) and many sparsely populated parts. The geographical position of an agent later on plays a role in setting up the social network.

The agents' tanking behaviour depends on their travel behaviour, the capacity of their fuel tanks C_i and their habits on when to refuel their tanks. The travel behaviour is modelled by means of a stochastic variable based on a normal distribution with agent-specific parameters for the expected value and the standard deviation. It determines the fuel consumption $c_{i,t}$ and, thus, the tank level

$$tank_{i,t} = tank_{i,t-1} - c_{i,t} \ . \tag{1}$$

Note that some consumers are rather cautious and therefore refuel their tanks within short periods of time while others stop by at petrol stations not until the fuel gauge forces them to. In order to set up a realistic scenario that avoids agents who either refuel their cars very soon after leaving a petrol station or regularly end up stranded with an empty tank, individual tanking thresholds are drawn from a Gaussian distribution.

Each agent has an individual information level $info_{i,t}$ (with $0 \leq info_{i,t} \leq 1$) on the innovation at hand (i.e., information levels can be associated with knowledge about a product). These levels may increase through word-of-mouth communication with other agents in the social network and/or as the result of exposure to marketing activities. Agents also have (individual) minimum information levels (in the sense of thresholds) that play a role in the purchasing process since agents are not willing to adopt new products as long as their information levels remain lower than their individual thresholds (cf. Homer, 1987). In our simulation runs, we initialise the minimum information levels with respect to the market segments an agent is assigned to: a rather low minimum information level is set for price-sensitive consumers and snob buyers since their adoption decision is primarily motivated by price. In contrast, quality-seeking consumers put a high emphasis on product quality and thus require extensive information about the product. This is also true for "eco-consumers", who base their purchase decision on the fuel's environmental compatibility. In addition to personal communication between agents in a social network, the information level is also positively influenced by the purchase of BioFiT, since this allows the customer to actually test the product and to form his/her own opinion (cf. Rogers, 2003).

Finally, each agent is set up with an influence level infl_i (with $0 \leq \mathit{infl}_i \leq 1$) that represents his/her expertise towards the innovation under consideration and is used for determining the amount of information received in word-of-mouth communication processes. For instance, it can be assumed that Formula 1 legend Niki Lauda is perceived as expert on fuels. If an agent personally knows Niki Lauda, he/she is prone to pay more attention to his opinion about biofuels than to the recommendation of a friend who has just happened to see some TV commercials on biofuels recently.

4.2 Social network

Agents are connected to each other through a social network where nodes represent agents and edge weights determine the probability that communication actually occurs between two agents. Since the topology of the network may considerably affect the pace of the diffusion process, our tool offers several alternative approaches for network generation: random networks (e.g., Erdös and Rényi, 1960; Newman *et al*, 2001; Strogatz, 2001), small-world networks (e.g., Watts and Strogatz, 1998) and the newly developed, so-called preference-based networks. In the latter, connections between agents are initialised with respect to geographical proximity (i.e., the smaller the Euclidean-distance pos_i and pos_j the more likely there is a connections between agents i and j; cf. Allen, 1978) as well as with respect to cognitive proximity which we assume to be high between agents of the same consumer type (following Nooteboom, 1999). Furthermore, agents with a large number of connections and/or agents with a high influence level (e.g., experts) can be added to the network. Note that opinion leaders – i.e., agents with many connections as well as high influence levels – are important catalysers for the information diffusion process within a social network and, thus, constitute an interesting target group for activities aiming at accelerating the diffusion process (Aaker *et al*, 1992).

4.3 *Information transfer*

Word-of-mouth communication has a major impact on purchase decisions (Brown and Reingen, 1987; Baxter *et al*, 2003; Mourali *et al*, 2005). In our simulation, communication starts once a communication event is triggered between two agents i and j which is the case if the random number that was drawn for that connection in a given period is lower than the edge weight. We assume that the agent with the lower information level learns from the agent with the higher information level. Thus, if $info_{i,t-1} < info_{j,t-1}$, the information level for agent i is updated to

$$info_{i,t} = info_{i,t-1} + infl_j \cdot \lambda \cdot \left(info_{j,t-1} - info_{i,t-1}\right) \tag{2}$$

where parameter λ $(0 < \lambda < 1)$ represents a learning factor. Otherwise, $info_{j,t}$ is updated in an analogous way. Note that the model also considers the decay of knowledge. To this end, values $info_{i,t}$ for all agents i whose information level has not been updated within a given number of periods are multiplied with a factor $1 - \rho$ $(0 \leq \rho \ll 1)$. However, we are aware of the fact that our approach in its current version disregards the possibility that knowledge about a product typically comprises several (independent) product characteristics.

4.4 *Purchasing process*

In each period t, agents may not only communicate with each other, and, thus, increase their individual information levels, but also may purchase the new product if the following conditions are met: (i) they need to buy fuel (i.e., the variable referring to the tank level $tank_{i,t}$ is lower than an individual threshold), (ii) they have sufficient information $info_{i,t}$ about the new product (where the threshold for "sufficiency" is set on an individual basis), and (iii) they want to buy the new product (i.e., their utility $u_{i,t}$ exceeds an individual threshold). Table 1 summarises the alternative purchasing scenarios.

In modelling the utility functions $u_{i,t}$, we use $K = 4$ weights $w_{i,k}$ where the first two refer to the price. For snob buyers, we set $w_{i,1} = 0$ and $w_{i,2} > 0$ and vice versa for all other consumers (i.e., $w_{i,1} \cdot w_{i,2} = 0$). The third weight $w_{i,3}$ represents the preference for quality and the fourth weight $w_{i,4}$ stands for the willingness to seek for fuels made from

Need to buy	Sufficient info	Want to buy	Product
Yes	Yes	Yes	BioFiT
Yes	Yes	No	Fossil fuel
Yes	No	Yes/No	Fossil fuel
No	Yes/No	Yes/No	No purchase

Table 1: Purchasing scenarios.

renewable energy sources. The utility function then takes the form

$$u_{i,t} = (1 - Price_t) \cdot w_{i,1} + Price_t \cdot w_{i,2} + ppq_{i,t} \cdot w_{i,3} + w_{i,4} \tag{3}$$

with $0 \leq w_{i,k} \leq 1$ and $\sum_{k=1}^{K} w_{i,k} = 1$ for each agent i. Parameter $Price_t$ represents the price of BioFiT that has been normalised with respect to lower and upper bounds of BioFiT's possible price range based on an exploratory empirical study. Thus, it is ensured that $0 \leq Price_t \leq 1$. Alternatively, we could have derived values for $Price_t$ from the price difference between BioFiT and fossil fuels and properly normalise it.

An agent wants to buy BioFiT if the utility values $u_{i,t}$ exceeds a personal utility threshold that was drawn through initialisation from a uniform distribution. Otherwise, the agent purchases fossil fuels. The personal utility threshold can be interpreted as the agent's innovativeness (cf. Rogers, 2003). Accordingly, consumers with a low utility threshold can be considered innovators, whereas those with a rather high one represent the laggards in adopting a new product.

If agent i makes a purchase in period t, the tank is refilled to its capacity, i.e., variable $tank_{i,t}$ is set to $tank_{i,t} = C_i$, and, if the agent has purchased BioFiT, the variable referring to the perceived product quality $ppq_{i,t}$ is updated to

$$ppq_{i,t} = \frac{\alpha \cdot ppq_{i,t-1} + TQ}{\alpha + 1} \tag{4}$$

where parameter TQ stands for the true quality with $0 \leq TQ \leq 1$ and parameter $\alpha > 0$ determines the pace for approaching TQ. Since BioFiT has strongly superior quality compared to (standard) fossil fuel, we set $TQ = 1$, which may not be the case for different products in other applications.

For statistical purposes, the binary variable $buy_{i,t}$ is set to $buy_{i,t} = 1$ in case that BioFiT has been purchased (while $buy_{i,t} = 0$ otherwise). Variable $sales_t$ summarises the (re-) purchases of BioFiT:

$$sales_t = \sum_{i=1}^{N} buy_{i,t} \tag{5}$$

New product adoption is traced through variable $adopt_{i,t} = \max\left(adopt_{i,t-1}, buy_{i,t}\right)$ being initialised as $adopt_{i,0} = 0 \ \forall i$. The total number of (first-time) adopters in period t then can be calculated as

$$adopt_t = \sum_{i=1}^{N} \left(adopt_{i,t} - adopt_{i,t-1}\right) \ . \tag{6}$$

4.5 Marketing activities

Marketing activities implemented in our simulation can roughly be divided in two groups. Activities of the first kind aim at increasing the information levels $info_{i,t}$ of a sample of agents i. These activities l $(l = 1, \ldots, L)$ may vary in several respects, namely, (i) their timing (e.g., they are active in a given time period, in a given number of succeeding periods starting with a designated time period or in several waves where the beginning as well as the length of each wave can be defined separately), (ii) the basic set M_l representing agents that potentially come in contact with the marketing activity (e.g., all N agents in case of a mass communication activity or just the agents located near a selected city in case of a geographically targeted activity), (iii) the (stochastic) variable determining the number of agents that are drawn from M_l in order to receive set $M_{l,t} \in M_l$ of agents that are actually affected in time period t, and (iv) the stochastic variable determining the (individual) impact of the activity, i.e., the value $info_{l,i,t}$ that is added to the current information level such that

$$info_{i,t} = \max\left(info_{i,t-1} + \sum_{l=1}^{L} info_{l,i,t}, 1\right) \quad \forall i \in M_{l,t} \ . \tag{7}$$

Note that in case an agent i is involved in word-of-mouth communication in time period t as well, we first perform calculations following Eq. (7) before updating the information level following Eq. (2) in a slightly modified form (i.e., by referring to the interim value for $info_{i,t}$ received from Eq. (7) instead of $info_{i,t-1}$). Further note that $info_{l,i,t}$ may also be modelled as an S-shaped (e.g., logistic) function depending on the information level

$info_{i,t-1}$ which ensures that for rather uninformed consumers as well as for experts the increment of information takes place at a slower rate following the idea of "learning curves" as proposed, for instance, by Chen and Edgington (2005).

Marketing activities of the second group are directed towards global parameters. First and foremost this concerns parameter $Price_t$ that may be altered in any period and directly affects a consumer's utility function $u_{i,t}$ (cf. Eq. (3)). In principle, we also could simulate effects of product enhancements or deterioration (e.g., as a result of blending BioFiT with conventional fuels). This may result, for instance, in different values for the true quality TQ.

The above described options make it possible to model marketing activities ranging from mass communication (e.g., television advertising campaigns) with huge sets M_l, much smaller, but still large, sets $M_{l,t}$ and small values for $info_{l,i,t}$ towards precisely targeted events where set M_l comprises just few agents, most, if not all, of them are selected in $M_{l,t}$ and they are subject to considerable increases in their information values. All of the above marketing activities aiming at increasing the information levels may be combined with each other and/or with pricing policies. Thus, a wide variety of marketing strategies can be simulated.

5 Simulation results

To the end of demonstrating the practical applicability of our agent-based simulation tool, we have set its parameters with respect to the aforementioned case study of the biomass fuel BioFiT and exemplarily investigate the influence of selected marketing strategies, namely, (i) mass communication with different timing patterns, (ii) targeting experts in the social network with or without additional mass communication, (iii) targeting consumers in different geographic regions, and (iv) implementing different pricing strategies (i.e., penetration vs. skimming). For each scenario we use $N = 10{,}000$ consumer agents, trace the development of variables over $T = 3{,}000$ periods and determine average values out of 2,000 runs. For illustration purposes, the retrieved scatterplots have been transformed to graphs using the spline smoother available in the statistical software R.

The impact of different marketing activities on the diffusion of BioFiT is measured in terms of the percentage of first-time adopters (i.e., $(adopt_t/N) \cdot 100$ with $adopt_t$ being the number of adopters in period t; cf. Eq. (6)) on the one hand as well as in terms of the number of BioFiT purchases (i.e., $sales_t$; cf. Eq. (5)) on the other hand. As adoption obviously serves a purpose beyond adoption itself, these measures may be supplemented by measures referring to profit or, for instance, the (positive) environmental effects of BioFiT that can be easily calculated from variable $sales_t$ once proper parameters (e.g., variable and fixed costs or the savings in CO_2 emissions per litre of biomass fuel) have been determined.

The simulation results not only follow the general behaviour pattern expectable for diffusion processes, but also have passed a "face validation" in which we have asked experts whether the model behaves reasonably (for subjective validation methods cf. Balci, 1998). Beyond that, a formal empirical validation (for a survey of empirical validation of agent-based models cf., e.g., Kennedy *et al*, 2006; Yilmaz, 2006; Fagiolo *et al*, 2007, or the respective website of Tesfatsion, 2009) could not be performed, mainly because of the lack of reliable field data.

5.1 Timing mass communication

More often than not, timing of marketing activities is crucial for the successful market introduction of a new product. We therefore compare two mass communication activities that both start at time period $t = 1$ and in each period reach 2 % of agents for a total of 30 periods, but differ in their scheduling. While the continuous activity constantly offers product information through periods $[1; 30]$, in the case of the intermittent mass communication activity (cf. Wright, 2000) consumers are exposed to the campaign in six intervals with a length of five periods each followed by 25 inactive periods, i.e., agents are confronted with information about BioFiT in periods $[1; 5]$, $[31; 35]$, $[61; 65]$ and so forth.

It turns out that the intermittent mass communication activity leads to an earlier takeoff and a faster gain of product sales than the continuous one (cf. Figure 2). This can be attributed to network effects, since distributed information is reinforced by word-of-mouth during the inactive periods, which then leads to a higher product awareness during the following advertising waves.

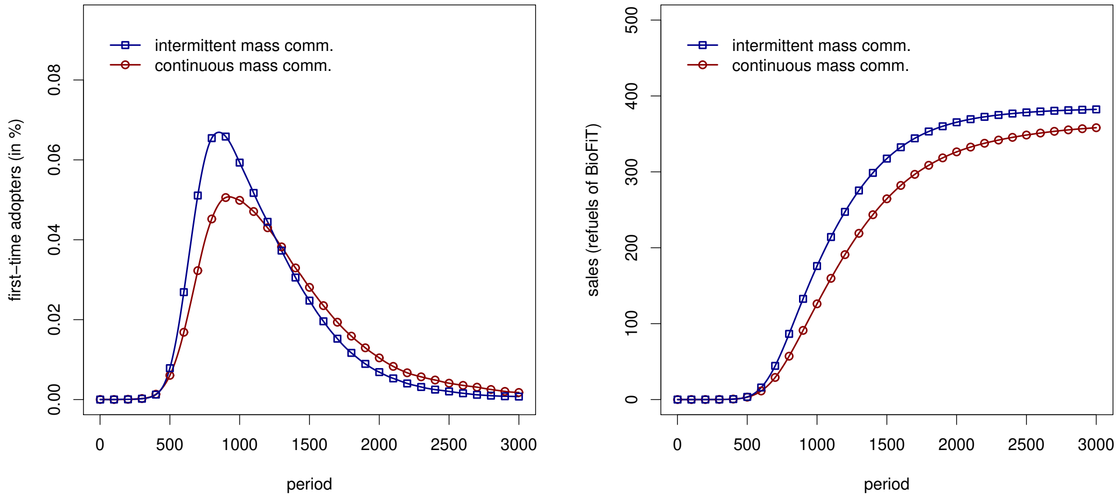

Figure 2: Timing of mass communication.

5.2 Targeting experts

The effect of a marketing campaigns may be enhanced when targeting people with specific characteristics such as their individual preferences (consumer types), their role in the social network (opinion leaders, experts), or the geographical region they are located in. In our "targeting experts"-scenario we therefore investigate the impact of an one-time event that takes place in the first time period ($t = 1$) and reaches less than 0.4 % of agents who are selected with respect to their (high) influence level (i.e., agents for whom $infl_i \geq 0.7$). Note that addressing opinion leaders (i.e., experts who also have numerous connections in the social network) would have been even more effective, but we assumed that identifying proper opinion leaders could become difficult in many practical applications (since their degree of connectivity with the social network often is concealed for outsiders) while firms usually either have a database of experts available or may identify them at comparatively low costs (e.g., through pyramiding as suggested by von Hippel *et al*, 2008).

Simulation results for our application case indicate that targeting experts and offering them substantial information about the new product (i.e., increasing their information levels by rather high values $info_{l,i,t}$) is a quite effective measure that considerably accelerates the diffusion process (cf. Figure 3), because the experts very effectively spread out information about the product to other potential customers. This may be further enhanced by combining targeting experts with a continuous mass communication activity as described above. However, it should be kept in mind that arranging an event (or setting up an analogous activity) as well as winning experts as participants for the event can turn out to be rather costly.

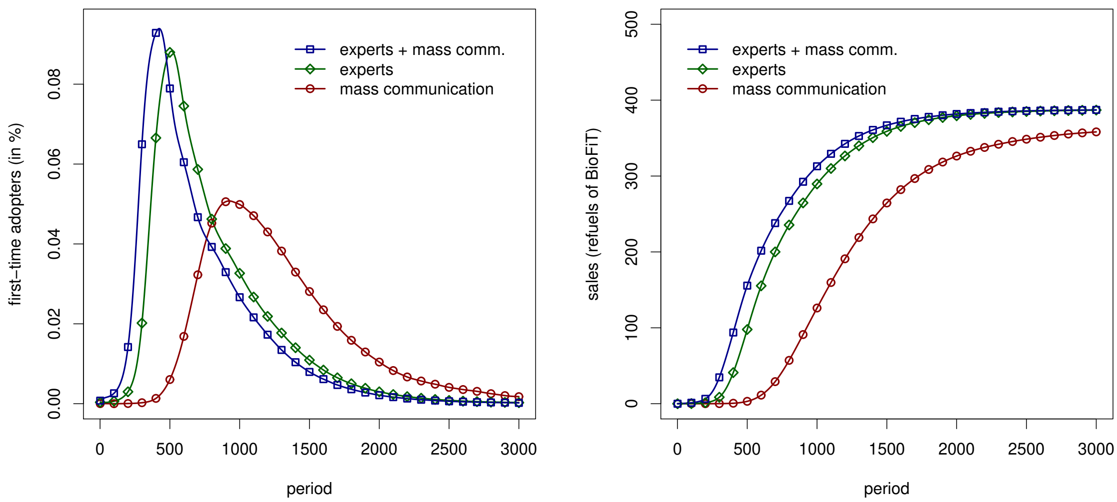

Figure 3: Targeting experts.

5.3 Targeting consumers in different regions

Our simulation tool also makes it possible to visualise the effects of geographically-driven activities. To this end, we launch direct marketing activities targeted at consumers situated in a smaller Austrian city and do the same for a larger city. In order to allow for a fair comparison, we assume that the same number of media contacts is established for both scenarios.

Given our parameter settings, targeting the smaller region results in a faster diffusion as well as more BioFiT sales (cf. Figure 4). This outcome is particularly influenced by social interaction between consumers since people in a small region talk to each other more often which leads to a stronger increase in their information level. The critical mass causing product takeoff is thus achieved faster than with targeting consumers in larger regions. However, it has to be taken into consideration that the impact of regional activities is strongly dependent on the character of the marketing activity. If, for instance, a company positions a billboard in the main street of a major city, on average more potential customers will be put in contact as compared to a smaller city.

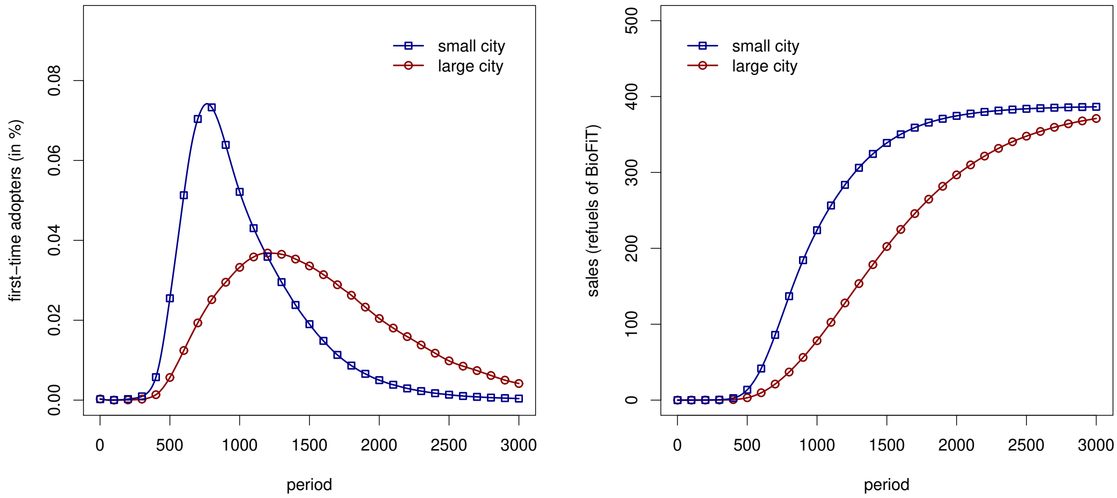

Figure 4: Geographically targeted activities.

5.4 *Pricing*

Since agents in our computer simulation simply are not aware of the existence of BioFiT if they are not provided with at least minimum product information, all pricing strategies must be accompanied with adequate promotional activities. Therefore, we combine two pricing strategies, namely skimming and penetration pricing, with the continuous mass communication mentioned in the first scenario. In case of the skimming strategy we start with a price at 120 % of the product's reference price (used in the scenarios described so far) for the first third of the simulation horizon (i.e., in periods [1; 1000]) in order to reach consumers who are willing to pay even a premium price for the new product (e.g., quality-seeking buyers or snob buyers). During the second third of each simulation run, the price is step-wise lowered to 90 % (i.e., set at 117 % for periods [1001; 1100], 114 % for periods [1101; 1200] and so forth) and during the final third remains stable at 90 % of the reference price. In the runs featuring the penetration strategy, the product's price is set to a constant level at 90 % of the reference price from the beginning in an attempt to maximise sales volume and market share (cf. Solomon and Stuart, 2003).

We found that the skimming strategy yields the highest total number of adopters (i.e., $\sum_{t=1}^{T} adopt_t$), because it attracts more consumer types. While quality-seeking buyers and eco-consumers are addressed by all three strategies, the skimming strategy additionally attracts the snob buyers since price is high at the beginning. From time period 1000 onwards, the price goes down, and also agents with a higher level of price sensitivity purchase BioFiT. The stepwise winning over the (large) segment of price-sensitive consumers is depicted in Figure 5 where the graph representing the first-time adopters for the skimming strategy has several peaks that clearly correlate with the steps of price decrease. However, the skimming strategy lags behind the results achieved by means of the penetration strategy with respect to the total number of purchases (i.e., $\sum_{t=1}^{T} sales_t$), because it requires more time before reaching a comparable market share if the largest consumer segment is tackled last. Nevertheless, profitability turns out to be higher when applying the skimming strategy than for penetration pricing (i.e., measured in terms of $\sum_{t=1}^{T} sales_t \cdot (Price_t - Costs)$ where the parameter value for $Costs$ has been estimated by our project partner from the Vienna University of Technology). In this respect, the strategy of staying with the reference price yields the highest profit. Thus, it can be shown that furthering product diffusion (e.g., by means of skimming) and/or increasing sales (e.g., by implementing a penetration strategy) may well come at the price of lower profits.

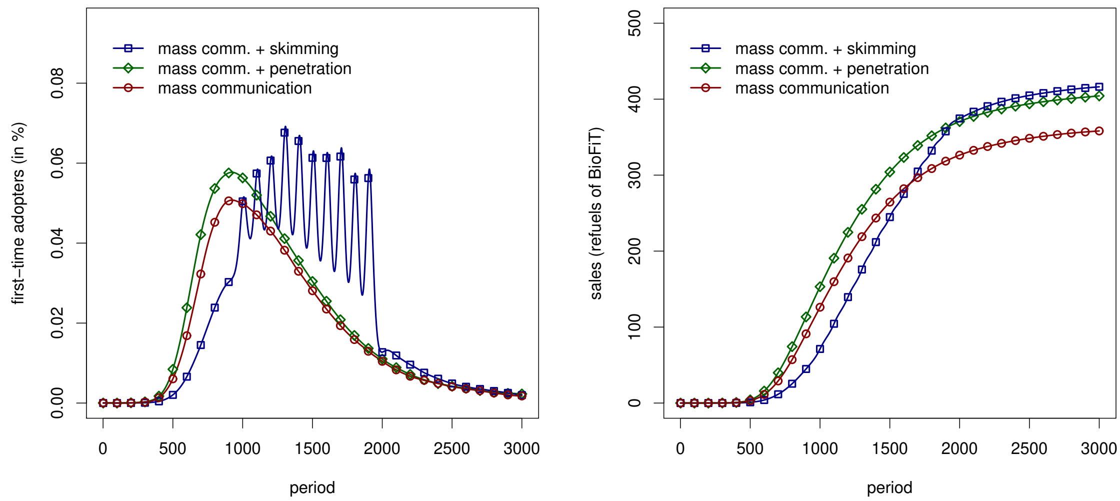

Figure 5: Pricing strategies.

6 Conclusions

Innovations and their diffusion on markets have a major impact on a company's long-term success. When introducing new products – such as a novel biomass fuel – on the market, (costly) marketing activities are required to further the diffusion of these products. Obviously, managers want to learn about the impacts of these activities beforehand. To this end we have developed an agent-based computer simulation that not only has potentially high practical relevance, but also is positioned at the thrilling interface between operational research, innovation management, marketing, and sociology. While related approaches typically investigate the effects of isolated factors influencing the diffusion of innovations (e.g., mass communication, consumer heterogeneity, network structures), our simulation approach also allows simulating the impact of (combinations of) clearly defined marketing activities (e.g., continuous vs. intermittent mass communications activities, targeted activities and/or pricing strategies) on the diffusion process of an actual innovation. It also takes into account consumer preferences, social interactions as well as the transfer of word-of-mouth in a social network. Furthermore, we modelled different types of consumers (e.g., opinion leaders) in the diffusion process and took into explicit consideration spatial effects in investigating geographically targeted marketing activities. The integration of both product-related characteristics (e.g., product quality, price) and consumer-related characteristics (e.g., preferences) represents another contribution of this paper, meeting the demand for strengthening of supply-sided factors in the analysis.

However, further research may be conducted in several directions. First, the number of product attributes may be expanded. Currently only product price, quality and environmental friendliness is considered which could be supplemented by fuel characteristics such as product brand, type of commodity, or efficiency. Next, awareness for as well as observability of product attributes may be taken into consideration. Furthermore, the communication process might be modelled in more detail and, thus, may take into account attribute-specific communication between consumers. Analysing the impact of network dynamics such as the creation of new edges during the runs as a result of marketing activities (e.g., consumers get to know each other at a company event and start to talk about the product) may constitute another interesting field of further research.

Then, measures may be added (e.g., for environmental effects) or calculated more accurately (e.g., regarding costs for which we have widely neglected economies of scale so far). Moreover, additional supply-sided model extensions may incorporate differing levels of availability of the innovative biomass fuel at petrol stations which will require the modelling of varying individual mobility patterns of consumers when choosing their point of sale. Finally, finding means for an empirical validation of our agent-based simulation approach for new product diffusion will remain on the agenda for further research as an important but also challenging entry.

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