Diffusion of Multiple Technology Generations: An Agent-Based Simulation Approach

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***Abstract*--Agent-based modeling has recently gained much attention in innovation and technology diffusion research. It enriches traditional approaches (like the well-known Bass model, based on differential equations) by modeling the diffusion process from a micro-level perspective. This allows, for instance, for considering the heterogeneity of consumers, who differ in their preferences, are distributed across geographical regions, are connected to each other in various ways within a social network, and act as well as react based on limited information. Although multiple successive technology generations got some attention in innovation and technology diffusion research using traditional approaches (since the Norton-Bass model in 1987), agent-based models have hardly focused on this important aspect of the diffusion process. Therefore, the presented agent-based simulation aims at investigating the diffusion of new products from multiple successive technology generations. The model accounts for novel product features in each generation, normative influences, and a social network that reflects both, spatial and social proximity between consumers. A historical validation is conducted by replicating the diffusion of computers (desktops, notebooks, tablets) on the German market from 1994 to 2013.**

I. INTRODUCTION

The market for high-technology products *"is characterized by waves of new product introductions and improvements"* [1]. These continuous improvements create successive generations, where *"each succeeding generation offers some innovative performance enhancements, feature additions etc. distinguishing itself from the past releases"* [2], while the core functionality of the original product stays the same [3]. Not only do customers benefit from the introduction of new product generations. If a company is able to commit to the future product and pricing strategy, a sequential strategy in terms of product introduction can be rewarding [4]. For instance, the semiconductor chip maker Intel typically introduce technologically-advanced generations every three to four years and thus reaching relatively higher prices [5]. These continuous innovations lead to shorter product life cycles, more intensive competition and therefore growing interest of companies to introduce not only a single generation but successive generations of high-technology products [6]. When introducing these innovations to the market, appropriate strategies for pricing, distribution and communication need to be selected. Such decisions require a thorough understanding of consumers' preferences, consumption patterns, and word-of-mouth referral behavior, which together with the firm's strategies leads to specific diffusion processes and eventually market acceptance of the innovation and the embedded technologies. Thus, models that can predict the impact of a chosen strategy on the diffusion of a new product are valuable tools for managing innovations and technologies [7]. Especially at early product development stages of (forward-looking) multiple generation product lines, various challenges like determining the introduction timing of each new generation, forecasting potential sales, or developing a dynamic pricing strategy for long-term profitability have to be met [3]. Additionally to the support in these managerial aspects and forecasting, mathematical diffusion models have proved to be good tools to explain the past purchasing-behavior or to observe general system behavior [2].

Traditional models based on differential equations (e.g. [8, 9]) model the diffusion process at the aggregate level of the entire population. Therefore, these approaches do not explicitly account for heterogeneity, like for consumers who differ in their individual preferences, behavior, expertise, geographical position, or connections between each other in various ways (for a discussion about the different levels of abstraction from macro-level to micro-level perspectives see [10] or [11]).

An agent-based approach can overcome such limitations as the modeling of relevant entities is done at the micro-level. These agents act and react to their environment and take decisions based on their limited available (local) information. All these actions (e.g., adoption of a product) on the micro-level lead to the emergent behavior (e.g., diffusion patterns) at the macroscopic level (also cf. [12-14]). Therefore, agent-based simulation is particularly suitable if interactions between consumers – such as communication within a social network – are of importance [15]. Additionally, it allows for capturing complex structures and dynamics without knowing the exact global interdependencies [10]). For a comprehensive survey of agent-based diffusion models and a discussion of their advantages see [16] or [17].

Although agent-based modeling has gained some attention when it comes to modeling general innovation and technology diffusion [16, 17], it has hardly been applied to multiple-generation diffusion. Therefore, we present an agent-based simulation that aims at investigating the diffusion of new products as well as technologies from multiple successive generations. The model accounts for (i) novel and/or advanced product features in each generation, (ii) interactions between multiple competing technologies rather than a fixed market potential for each innovation, (iii) repeat and postponed purchase decisions rather than only the initial adoption of consumer durables (for the necessity in fast-tech products and services like the computer market see [18]), (iv) normative influences, and (v) a social network that reflects both, spatial and social proximity between consumers.

Agent-based models are sometimes criticized as ‘toy models’ that do not adequately capture actual behavior in a real market setting, mainly because they lack of empirical foundation [19]. Therefore, the presented model will be validated for the case of desktop computers, notebooks and tablets using various data sources.

The paper is organized as follows: First, we give a brief overview to multi-generational technology diffusion. In section III, we introduce and describe the agent-based model and its core elements. The application case, the used data, the matching with the historical data as well as some exemplary analysis that are enabled by the agent-based approach are presented in section IV. Finally, the paper concludes with a brief summary, discussion of limitations and an outlook for further research (Section V).

II. MULTI-GENERATIONAL TECHNOLOGY DIFFUSION

The basic (‘classical’) diffusion process is determined by the decay of the number of new adopters and the saturation of the market potential. In practice, it is also determined by substitution with newer generations of products and technologies, more advanced attributes and/or new attributes. Especially high-technology products are introduced to the market in form of successive generations. These multi-generational product lines are formed by both, patterns of diffusion (for fundamental work refer to [9, 20, 21]) and patterns of substitution (first discussed by [22]). These two phenomena were combined for the first time by Norton and Bass [8] into a single model which is able to describe the sales growth phenomenon by considering different respectively separated generations simultaneously (for a discussion of the significance of this work see for instance [23]). Since then, the Norton-Bass-model was modified by various authors [24-38] or served as base and inspiration for new/other models coping the multi-generation phenomena in the (innovation/technology) diffusion process [2, 3, 5, 39-49]. Multi-generation aspects have also been applied to various application cases, including personal computers (e.g., [18, 24, 31, 36]), dynamic random-access memories/semiconductor industry (e.g., [8, 18, 36, 49, 50]), mobile phones/wireless communication (e.g., [27, 31, 35, 36]), fuels (e.g., [51]), copiers (e.g., [36]), video players (e.g., [52]) or fuel cell vehicles (e.g., [48]).

Hardly any study focuses explicitly on the adoption of product generations from an individual consumer perspective [52]. Kim, Srivastava and Han [53] use a logistical modeling framework to estimate the purchase probabilities for successive personal computer generations based on individual consumer data. They allow for initial and repeat purchases as well as leap-frogging behavior and take purchase history, buyer expectations of future generations, and preferences for currently available options into account. Van Rijnsoever and Oppewal [52] observe – using predictive models for early adoptions – by means of four generations of video player products, that the best prediction is possible if including both, the previous generation and socio/psychographic variables. Sääksjärvi and Lampinen [54] focus on the consumers adoption of a successive product generation based on perceived risk, which differs between generations based on the technological difference, and is (also) moderated by whether the consumer has usage experience of the previous generation. Resistances to innovation adoption is also taken into account by Zsifkovits and Günther [48]. As they use an agent-based approach, they explicitly consider the individual level. For the case of hydrogen vehicles they show that technological progress rises both, functional (usage barrier, value barrier, functional risk, and economic risk) and psychological barriers. By incorporating resistances arising from technological progress, they contrast the typical ‘pro-innovation bias’ of diffusion models [55]. In the same year, Kilicay-Ergin, Lin and Okudan [3] also published an agent-based simulation that discusses the multiple-generation product line problem by investigating various pricing strategies and the yielding lifecycle profitability under differing conditions.

Although various influencing research in the field of multiple technology generations could be identified, [52] indicate that *“adoption patterns of successive product generations are not well understood”*. Especially when it comes to integrating the individual consumer perspective and accounting for heterogonous consumer characteristics, our literature review spotted only two contributions [3, 48] that (quite recently) extended the research agenda of multiple technology generation diffusion by using an agent-based approach.

III. AN AGENT-BASED MODEL FOR MULTI-GENERATION-TECHNOLOGY DIFFUSION

Following Stummer, Kiesling, Günther and Vetschera [7], our agent-based model is based on the well-established conceptual model by Rogers [56] and distinguishes all five phases of the adoption or non-adoption of an innovation: (i) learning about the existence of an innovation and its basic functions (‘knowledge phase’), (ii) forming a favorable or unfavorable attitude based on information (‘persuasion phase’), (iii) decision to adopt or reject the innovation (‘decision phase’), (iv) actual use of the innovation (‘implementation phase’), and (v) seeking information to reinforce the decision (‘confirmation phase’). The presented model covers the complete process, including the two latter phases that are not considered in most previous agent-based models [7]. An overview of the main entities and the model dynamics is given in Fig. 1 and will be presented in the following chapter.

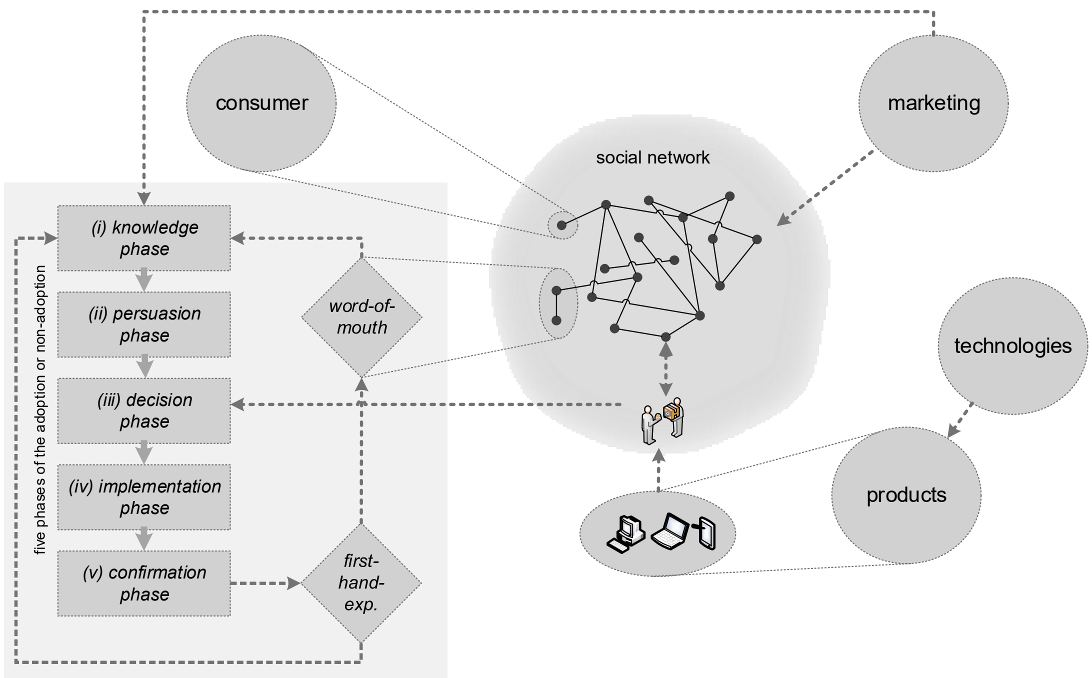

Fig. 1: Model entities and dynamics

A. Products and technologies

Several (technological) generations of products are successively introduced to the market. Each product is characterized by various attributes that differ concerning their performances. A newer generation of a product may not only perform better in previously introduced attributes (e.g., 'faster network connectivity'), but may also have new and additional attributes (e.g., 'internet-connectivity'). For instance, a desktop computer does not have the product attribute 'battery life' whereas this is an integral element of a notebook.

Every product's attribute has a true performance value (which might be positive or negative). This performance may not be instantly obvious or observable by the consumers. Once they have adopted the product, they learn about its characteristics through first-hand experience. This experience differs between consumers as well as attributes, as the perceived performance-information might not be objectively observable or is differently interpreted by the consumers. Therefore, the perceived value of each attribute varies within an ex-ante (and between attributes differently) defined interval about this true level. Additionally, each attribute can also differ in terms of the time span between the adoption of the product and the learning about the performance. For instance, the computing power can be observed quite quickly whereas the ability for a mobile use of a notebook might take some time to be realized.

Every product also has a pre-defined price, which varies over time. This allows for testing various pricing strategies. The products also have a date of market-introduction as well as its discontinuation.

Each product belongs to a (superordinate) technology, which allows for capturing diffusion patterns at the product and the technology level.

Note, even though more than one producer can be considered, competition between producers is not in the focus of this paper. The same applies for teething problems or error rates as well as for possibilities to fix these problems.

B. Consumers and the five phases of the adoption or non-adoption

Per se, consumers are not aware of all the available products, their attributes nor their performances ('true values'). Therefore, they need information about the currently available products (and their attributes). Consumers form their attitudes about the products during the *'knowledge phase'* [56] by either (i) being exposed to marketing activities (see sub-section 'marketing'), (ii) through their own, first-hand experience after purchasing (as described above), or (iii) by chatting with their peers (word-of-mouth).

Word-of-mouth communication between consumer-agents occurs based on an individual communication behavior (frequency) and, additionally, after a consumer gained new information about a product though personal usage (first-hand experience). Especially if personal experience with a product does not match the prior formed expectations, this can lead to disappointment and therefore to negative word-of-mouth. As negative word-of-mouth has a greater impact in the adoption process than positive (e.g., [57, 58]), and people weight negative word-of-mouth more than positive [59], negative product experiences lead to more communication events and negative information is weighted higher in our model.

Therefore, not every communication event has the same impact on forming the consumer's attitude towards a product. Additionally to negative information, consumers also value the received information based on the expertise-level of the sender. This means that information received from a computer expert has a greater impact than that of a novice.

Consumers can only possess one product at a time and they replace it occasionally based on an individual buying cycle. If such a need arises, they evaluate all available products they are aware of and, additionally, compare them with the one currently in use. Therefore, they seek for the relative advantage (one of the characteristics highlighted by Rogers [56]) of all available and known products, which Rogers refers to as the *'persuasion phase'*.

For the evaluation of a product, an additive utility function is used that consists of three (agent-individually) weighted parts. (i) First – which we refer to as the 'rational part' of the utility function – the (known) products attributes are taken into account. Remember, as consumer agents do not know the true attribute values, their estimates of the products characteristics are based on the previously received information through marketing campaigns, word-of-mouth, or – if the product has previously been used – own first-hand experience. Note, not every consumer may be aware of all available products and/or their attributes. Beside the individual preference structure, we consider an additional innovativeness factor. Consumers with a higher level of innovativeness can be characterized as innovators, whereas those with a rather low value as laggards [56]. Additional to the rational evaluation, we consider also (ii) social influence as the second part of the utility function as most *"existing simulation models ignore social influences which may play a critical role in purchasing a product"* [60]. The influence on each consumer is calculated for each product in the evoked set as a fraction of the quantity of products in use divided by the numbers of peers of each consumer. Note, alternatively to other approaches (e.g., [60]), we consider only agents that know each other, thus, those who are socially connected.

Finally, the (obviously known) (iii) price is considered as last part of the utility function and has – at least in our application case – a negative influence on the utility function. Each of these three parts of the utility function (rational, social, price) are weighted individually for each agent.

In the *'decision phase'*, whether to buy or reject the product, a minimum utility value can be considered (most commonly a negative utility). This is especially of importance if people initially do not own a product that can be used for evaluating the relative advantage of the new product.

If the consumer rejects to buy one of the available products (under the assumption that the product is not broken, which would force the consumer to buy a new one), a new buying event in the nearer future will be scheduled as we assume that there is a greater need to replace the old product. This might happen as consumers evaluate the new products inferior to the one currently in use, but which is no longer available for repurchase. Otherwise, if the current product is still available, we do allow for repurchases (for the role of repeat purchases in the early generations of fast-tech products like computers ref. to [18]). Reason for a lower utility of a newer product could be that consumers do not have enough or accurate information about the new products, that they are not aware of all (new) attributes of the product (as they have not heard about it via marketing activities nor via word-of-mouth), that their preference structure leads to a lower evaluation of the new products, or that the product's utility is less than the minimum required (especially if consumer do not own a product in the beginning).

In the post-purchasing process, some time after consumers started to use the new product (*'implementation phase'* [56]), they learn more about the features (attributes) of the product and therefore get more information about the real performance of each attribute. This learning process might be different for each attribute in terms of time and observability. Some attributes might be more and/or quicker observable (e.g. performance of the computer) than others (e.g. battery lifetime). In addition, also the accuracy of the perception might differ. This first-hand experience eithers leads to reinforce the decision or to disappointment (*'confirmation phase'* [56]). In both cases, consumers start to share their experience within the social network via word-of-mouth. This social network reflects both, consumers (i) spatial and (ii) social proximity.

C. Social network

„A social network is a collection of people, each of whom is acquainted with some subset of the others" [61]. For generating a social network for an agent-based simulation for innovation diffusion, various algorithms like scale-free [62], random [63] or small world [64] exits. In their critics on neglected important variables of the diffusion process, Delre, Jager, Bijmolt and Janssen [60] point out that these (various) algorithms for generating network structures are still very simple and do not reflect realistic consumer networks. For instance, they usually do not account for the geographic location of agents, although spatial distance between members of a social system correlates strongly with the propensity to form bonds and exercise influence on each other (cf. [65]). Therefore Kiesling, Günther, Stummer, Vetschera and Wakolbinger [66] (and later more extensively described by Stummer, Kiesling, Günther, Vetschera [7]) adapt the algorithm by Barabási, Albert and Jeong [67] and extend the method of Manna and Sen [68] in order to consider geographic distance. For suitable parameter values, this algorithm allows for graphs that exhibit the characteristic features of social networks (i.e., small diameter, high clustering and scale-freeness [7]). In addition to the number

of edges and the distance between the vertices of the graph, we extent the algorithm by additionally considering cognitive proximity (for an earlier approach for connecting geographic and cognitive proximity refer to [69]). We therefore assume a higher connection probability between agents of the same consumer type (following [70, 71]) and at a closer geographical proximity (following [72]).

D. Marketing

The objective of marketing events is to make consumers (i) aware about new products and attributes and (ii) to inform them about the performance concerning the products' attributes. Therefore, each marketing event is characterized by the targeted product and topic (attribute) as well as the content (information about the performance, which might also be exaggerated compared to the true value). Additionally, the period of activation as well as the targeted number of consumer agents have to be specified. The impact of marketing activities is typically smaller than that of word-of-mouth [73] and therefore consumer agents attach less weight to this kind of information compared to inter-personal communication.

The currently implemented marketing type corresponds to mass media advertising, but others might be considered in the future with little implementation effort (e.g., advertising at the point-of-sale). Also for simplification and due to lack of empirical data, the marketing measures are directed towards a random set of the entire population, but could also be restricted to a specific geographical area or consumer segment.

IV. SIMULATION RESULTS

The model was implemented in AnyLogic 7.0.3. For the analysis of the results, additional programs like R (including the package 'igraph') were used. Additionally, a program for automating the analyzation process was written based on Microsoft .NET.

The applicability of the agent-based model is illustrated and validated for the German (privat) consumer market of personal computer, notebooks and tablets. Historical sales data are publicly available through the 'Consumer Electronics Market Index Germany' (CEMIX) for the years 2005 until 2013 [74]. Additional data was received for the years 1994 to 2004 by the same publisher via personal correspondence, as these years have not been published on the website.

A. Parametrization

Especially when it comes to define the different technological and product generations, definition and classification becomes difficult. Most contributions so far have solely focused on technological parameters (like model/processor type), also if they take a (heterogeneous) consumer perspective (e.g., [53]). As we emphasize a strong focus on the consumers' perspective, we argue that consumers identify new product generations based on various product characteristics (attributes) like computer performance (which might correspond to the processor type), mobility behavior, battery life, and (internet) connectivity. Like this, different product generations are formed (like 'computer without internet and first generation of graphical user-interface' followed by 'computers with first-generation internet access and advanced graphical user-interface'). These product generations are then classified into the more broaden technologies 'desktop-computer', 'notebooks' and 'tablets'. Like this, seven different product generations of the technology 'desktop-computer', four generations of 'notebooks' and one for 'tablets' have been identified. To our knowledge, this distinction into various products and corresponding technologies have not been considered so far. The increase of the products' attributes between generations (representing the technological progress) follows the s-curve phenomenon [75]. Therefore, the increase in performance of a technology is initially slowly, speeds up in the middle range of the s-shaped curve as the technology is better understood and more often applied. Thus, the performance increases more rapidly as the technology reaches its most well developed shape. As the technology matures, improvements become increasingly difficult and expensive and therefore the performance increases taper off (e.g., [75, 76]).

The advanced generation does not replace the existing product immediately. Following Kapur, Chanda, Tandon, and Anand [34], they are usually introduced to the market before its predecessor already diffused completely among its adopters thus starting to compete with the existing one and provoking a cannibalization effect (for an example of Microsoft Windows operating systems XP, Vista and 7 refer to [77]).

The consumer agents were initialized with an individual and unique set of characteristics each based on predefined groups according to Rogers [56] five groups of consumers: innovators (2.5% of the population), early adopters (13.5% of the population), early majority (34% of the population), late majority (34% of the population), and laggards (16% of the population). Even though each consumer agent is individual concerning the actual set of characteristics and parameters, they correspond to one of those groups and therefore shares similar habits. For instance, innovators are highly interested in new developments and distinguished by readiness to take hazards [56]. The group of early adopters often act as opinion leaders and spread new information, ideas and norms within a social system. Therefore, they help to form a critical mass, which enables the diffusion process to become self-sustaining [52, 78]. They act as role models for those individuals who have not adopted the innovation yet. In order to represent this influence on later adopting groups in the simulation experiments, early adopters are initialized with a high expertise level. In contrast, the late majority typically takes a skeptical view towards innovations. Thus, they generally consider adopting an innovation when the bulk of consumers already uses the novelty [56]. Therefore, this group of agents is highly exposed to social influence by its peers. This is even stronger for the laggards, who typically wait until a technology is ‘state of the art’ and has diffused through the bright mass of the population [56].

For setting the communication parameters (especially the positive and negative word-of-mouth) we refer to [57-59, 79-81]). The generation of the social network is done by using the proposed and tested parameters by Stummer, Kiesling, Günther and Vetschera [7]. The presented scenario therefore does not account explicitly for the cognitive proximity.

Like described above, most of the parameters could be identified using empirically or theoretically driven sources. If no information was available (e.g., coverage of marketing activities for each product), various extensive simulations runs were performed and robustness analysis were executed. An overview of the sources for parametrization are given in Table 1 and Table 2.

Results and validation

Each simulation-run consisted of 10,000 consumer agents and was repeated fifty times using different seeds. The analyzed time horizon is 20 years and one year corresponds to 10 periods. Even so no empirical data was available for the first years after the market introduction of personal computers, we simulated additional (and not analyzed) 100 periods in advance in order to reach a reasonable number of adopters at the end of 1994 (corresponding to period 110). Sales-figures and the number of agents where scaled down to reasons of computability by the same factor (0.000303). Although sales-figures were available through [74], the number of users had to be estimated by using [85][1].

TABLE 1: SOURCES OF PARAMETERS: CONSUMER AGENT

type	parameter	empirical/ theoretical	runs	sources
utility	price	X		[56]
	attribute preferences		X	-
	social influence	X		[52, 56, 78]
	innovativeness	X		[56]
buying	buying rate (normal)		X	-
	buying rate (short)		X	-
word-of-mouth	communication frequency, disappointment	X		[57-59, 79-81]
opinion-leadership	influence based on expertise level	X		[52, 78, 82]
influence	first-hand-experience	X		[83]
	word-of-mouth, marketing	X		[71, 73]

TABLE 2: SOURCES OF PARAMETERS: NETWORK, PRODUCTS AND MARKETING

type	parameter	empirical/ theoretical	runs	sources
network	α, β, n^{link}	X		[7]
products	availability (from), technology	X		[18, 74, 84], various websites
	availability (till)		X	~
product attributes	(internet) connectivity	X		[18], various websites
	performance (desktop/notebooks)	X		various websites (e.g. Intel)
	mobility		X	-
	battery life	X		various websites
	price	X		[74]
marketing	strength of marketing		X	-
	coverage		X	-
	timing information		X	-

[1] In order to estimate the number of current users of any computer technology for the last year of observation, we calculated $\frac{(number\ of\ German\ housholds \cdot percantage\ of\ housholds\ with\ a\ computer \cdot number\ of\ computers\ per\ houshold)}{average\ number\ of\ people\ per\ houshould}$. This was the best available approximation for the maximum number of users.

According the advice of Macy and Willer [15] to *“experiment, don’t just explore”*, various different parameter constellations were systematically tested. The fit between the empirical data and the agent-based simulation can be seen in Fig. 1. The results fit the real-world data especially good in the beginning of simulation. Although still very accurate, it shows some slightly differences for the last three years. Interestingly we notice that towards the end of the simulation the marketing efforts need to be higher in terms of total numbers of contacted consumers per product in order to match the trend of the real data (see Fig. 3). This is not only induced by a higher number of contacts per period, but also due to an extended execution time of each marketing activity. Despite for the last product of each of the three technologies, marketing activities were fixed to 22 periods, which is in average half of a product’s lifetime.

Having three competing technologies in the end makes marketing of a greater importance in order to stimulate the consumers to buy one of the products. As we have learned from our experiments, it is not only the competitiveness between these products itself (remember, each consumer can only possess one product at a time). Typically, diffusion models suggest pushing a new product into the market through elaborate marketing activities. This holds also true for the results from our simulation experiments, as it is necessary to inform people about the product and its (new) characteristics. But it can be seen – at least from the simulation results of this application case – that it seems easier to compensate a lack in technology (as in the beginning of a technology) through marketing measures as compared to a market, where consumers have already experience and an attitude towards a technology.

Even though there is significant technological progress for all the three latest launched generations, they do not contain any new attributes. Additionally, these last products of each technology are also longer on the market than its predecessors. This missing progress might be a reason for the slower growth in terms of sales. On the other hand, the decline of desktop computers is due to the cheap availability of additional product characteristics in the other technologies. We can see that the decline in price is a serious enabler of the technology, especially if we regard the rise of the technology notebooks. Average price of a notebook was about twice compared to a desktop computer until 2002. By 2009 the price for notebooks was even less than that of the competing technology.

Even sales data is available on quarterly bases and this agent-based model does not explicitly consider any seasonal effects (e.g., Christmas), this had no impact on the quality of the estimation. Although this accuracy is more than sufficient as the focus of such a model is the diffusion of the technology respectively the corresponding products, this is a quite interesting aspect when it comes to predicting a future trend by using this methodological approach.

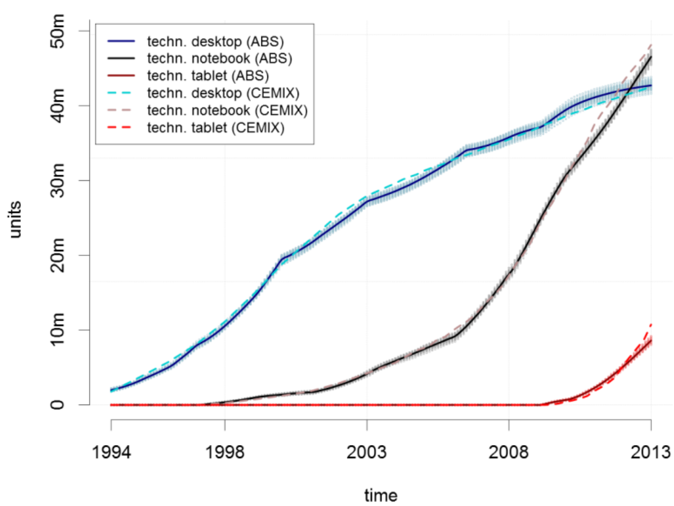

Fig. 2: Sales – fit of simulations results and empirical data (up-scaled to real values)

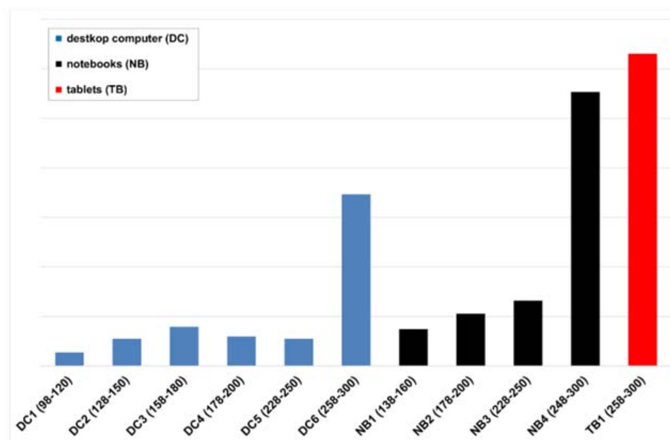

Fig. 3: Marketing effort per product

Although we cannot match real adoption data with our simulation results as adoption data for Germany is only available on household level (and cannot be converted to an individual level), we want to show exemplarily (see Fig. 4) the adoption rate of the three different technologies, of any of those technologies as well as of mobile devices (notebooks or tablets).

Although agent-based approaches come at the cost of a greater number of parameters, it can offer additional perspectives and breakdown of data (e.g., per consumer-type, per technology in use, per region). Furthermore, additional simulation outputs would allow to match against various data sources (e.g., sales, adoption, and products in-use) for the historical validation; availability of data assumed. This could even increase the accuracy of the parameter-estimation.

Based on our results we can summarize that the presented agent-based model of multi-generation technology diffusion is accurate and valid for the chosen application case.

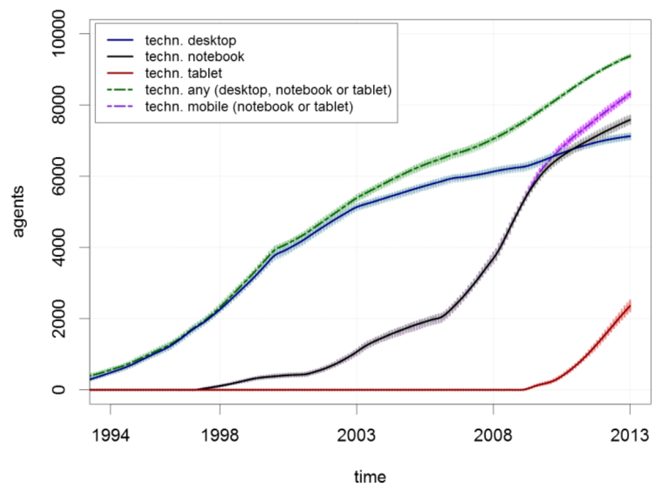

Fig. 4: Adoption rates

V. CONCLUSIONS

In this paper, we introduced an agent-based model that depicts the complex diffusion process of (competing) multi-generation technologies and corresponding competing products. Our model accounts for repeated purchase, competing technologies, the whole adoption process on the individual level, leapfrogging, sales figures and adoption rate. We used the model to replicate the diffusion of three different computer technologies (desktop computer, notebook, and tablet) in Germany for the years 1994-2013. This historical data allowed proofing the applicability of the model through extensive testing using. Furthermore, it could be shown, that an increase of competing technologies demands for an increase in marketing efforts to comply the historical sales data. It seems easier to compensate a lack in technology (as in the beginning of a technology) through marketing measures as compared to a market, where consumers have already experience and an attitude towards a technology.

If new data becomes available, it will be interesting to see if the small deviation between the real data and the simulation output concerning the technology notebook is still present or if it is just – as expected – an artefact due to the longer availability on the market within this simulation scenario. Additionally, the model could be extended by the possibility of owning more than one product simultaneously. This seems especially useful as tablets become available, as this technology is used – more often than others are – additionally to a desktop-computer or notebook. Also the influence on and trigger of buying events could be another promising enhancement. A validation-process-related extension would be the automatization of the matching between the various parameter portfolios and the real data. This would not only bring more convenience, but would also allow for matching against miscellaneous empirical data (e.g., adoption rate, technologies in-use, sales). This could reduce the challenge that agent-based simulations might induce, as they typically demand for a higher number of parameters (compared to classical approaches). Some empirical data is available on individual, some on household-level. An integration of both layers would be interesting but at the same time quite challenging and demands for more and extensive (empirical) investigations, as currently no adequate data set is available.

The current implementation of the agent-based simulation allows for various additional research directions, so far not covered by other models. For instance, the influence of teething problems (failure rate/bugs and their fixings) on the diffusion process can be explored. Additionally, the developed network algorithm allows for capturing geographical as well as cognitive proximity between consumers. Finally, the model might also to be tested and applied to different cases (e.g., mobile phones) in order to get a broader validity of the model.

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