To Main Proceedings Document

The Diffusion of Goods Considering Network Externalities: A System Dynamics-Based Approach

Jörn-Henrik Thun, Andreas Größler and Peter M. Milling
Industrieseminar der Universität Mannheim
Schloss, D - 68131 Mannheim, Germany

Phone: (+49 621) 181-15 78, Fax: (+49 621) 181-15 79
E-mail: thun@is.bwl.uni-mannheim.de,
agroe@is.bwl.uni-mannheim.de,
pmilling@is.bwl.uni-mannheim.de*

Abstract

The diffusion of goods showing network externalities differs from that of conventional products. In particular, two effects are important: the bandwagon and the penguin effect. An incrementally refined system dynamics model helps to understand this special diffusion process better. Leverage points for the management of such products can be identified using simulation results.

In recent years, trends towards an information society have emphasized the importance of goods satisfying information and communication needs. Many products of this market segment, e.g. electronic mail, contain characteristics, which make a specific examination necessary. These characteristics are based on the fact that the utility of these products cannot be regarded as a constant value. In case of this specific type of products, utility is a dependable variable resulting in a distinct diffusion behavior.

The occurrence of a variable utility can be explained by a concept called "network externality". A product is characterized by a network externality, if the utility of a product is a function of the installed base. The utility of products including network externalities rises with this value leading to an interdependency of users. This interdependency is based on two properties of products with network externalities: the penguin effect and the bandwagon effect.

This paper examines the way how the diffusion of goods is influenced by these effects using the system dynamics approach. Based on the basic diffusion model of Bass, characteristics of network externalities are integrated successively to simulate the diffusion behavior of these specific goods. This analysis helps in understanding causes and effects of network externalities. After that, conclusions concerning successful diffusion strategies for these particular goods are derived from the system dynamics model. Starting points for further research are indicated at the end of this paper.

* The authors like to thank Frank H. Maier for his helpful comments during the model building process.

A Model to Calculate Product Diffusion

Historically, economic models of the diffusion of innovations are based on biological and sociological research. On this base, diffusion is defined as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers 1983). Although this general definition is valid for any kind of innovation, in this paper only the launch of new products in a certain market are investigated. Process, social, or organizational innovations are not considered.

In Roger’s definition, communication is the driving force that creates the wish to buy a product. Communication—seen as the exchange of information between members of a social system—initiates diffusion and influences size and speed of this process (Maier 1995). Models of diffusion, therefore, describe how communication drives diffusion; they are “the mathematical representation of the process of diffusion” (Kalish and Lilien 1986).

One of the best known diffusion models is from Bass (1969). As a mixed-influence model, it integrates effects of mass and impersonal communication (Mahajan and Peterson 1985). It distinguishes between two types of customers: innovators and imitators. Innovators become customers because they are interested in novelties. Imitators ground their decision to buy a product on the behavior of other members of the system. Bass formulates the following equation in order to calculate product sales *x* for a specific time period *t*:

$$x_t = \alpha(N - X_t) + \frac{\beta}{N} X_t (N - X_t)$$

N symbolizes the total market potential, X_t cumulated sales from period 1 to t-1. α and β are innovator and imitator parameter, respectively. They contain the weight of innovator or imitator influence on the diffusion process.

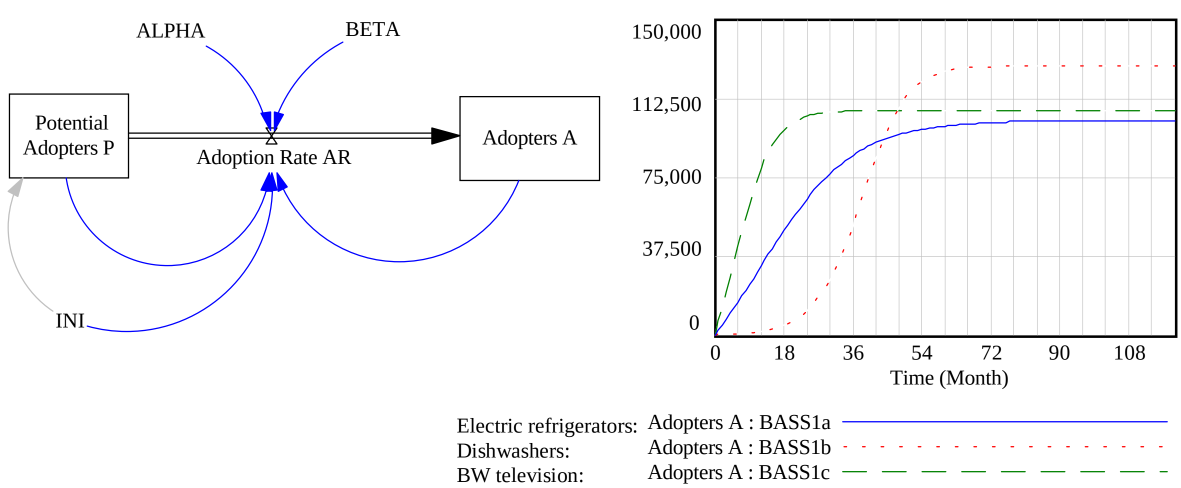

Figure 1: Simple “system dynamics model” to generate diffusion behavior1

A simple “system dynamics model” is able to generate different diffusion processes when the above given formula is used to calculate behaviors graphs (see Figure 1). In this figure, parameter settings for different products are used in accordance to Bass (1980). Nevertheless, as Milling (1996) and Maier (1998) clearly state, this kind of model gives (1) no explanation why diffusion actually occurs, and, (2) how the diffusion process can be influenced by management (e. g., using different price strategies). Sterman (2000) gives a basic feedback-oriented interpretation for the Bass model which consists of a balancing (advertising) and a reinforcing (word-of-mouth) feedback loop.

In this paper, we take Sterman's model of the Bass diffusion as a fundament that can be used to generate insights into the diffusion of a special kind of product innovations. In the rest of this work, only products are considered which show positive demand externalities, i. e. "the benefit to a consumer of a product increases with the number of other users of the same product" (Xie and Sirbu 1995). We aim to model the diffusion process based upon the decision process of individuals which have to decide buying and keep on using a product showing network externalities.

Characterization and Systematization of Products with Network Externalities

One can find many definitions for network externalities (sometimes also called "positive demand externalities") in the literature (see, e. g., Church and Gandal 1993, Katz and Shapiro 1985, Brynjolfsson and Kemerer 1996). As a basic definition it can be stated that network externalities exist if the utility of a product for a customer depends on the number of customers who have also bought this product. Network externality can be direct or indirect (Bental and Spiegel 1995).

The classical example for a product with direct network externalities is the telephone (Brynjolfsson and Kemerer 1996). The entire utility of a telephone system increases with the amount of feasible communications. Other, more up-to-date, examples for this kind of network externalities are e-mail, fax, certain web pages (opinion servers, auctions) etc. All of these products are designed to satisfy communication and interaction needs.

An example for goods characterized by indirect network externalities are personal computers. Although the degree of utility is not directly related with the amount of users of that product it nevertheless shows an indirect effect concerning utility: if many people use the same computer platform more software for the specific platform will be developed, bugs are found faster, and more external competence can be expected in case of problems (Xie and Sirbu 1995).

Another very important kind of products influenced by network externalities are cellular phones. At first sight, it seems to be that their network externality is direct, because a certain amount of users must be part of the network to built up a satisfying level of utility. Surprisingly, the network externality of cellular phones is indirect. The mobile communication network itself has the characteristic of a direct network externality. However, because of the compatibility to the conventional telephone system, the network externality is not direct. Due to the fact, that the accessibility and service rises with the number of users of a mobile communication network, the corresponding network externality is indirect.

Generally, contrary to conventional products, the utility of products influenced by network externalities depends on the installed base B_t which is defined as the cumulated amount of users at time t. Regarding products for which the network externality is direct, the utility is based on the level of the installed base exclusively. Then, the utility of a product is a function of the number of feasible interconnections I_t which depends on the number of users and the technological restriction r of a network. Thus, assuming that utility can only be derived from the number of interconnections, U_t can be calculated by the formula:

$$U_t = U_t(I_t) = \sum_{k=2}^{n} \binom{B_t}{r} = \sum_{k=2}^{n} \frac{B_t!}{r!(B_t - r)!}, \text{ whereby } r,\ B_t > 0.$$

The fact that the utility of a product depends on the interconnections, results in an interdependency of user, whereby the users find themselves in a utility network. If the achievable utility of a product depends on the network size, the adoption process of users depends on the decision of other potential users. This leads to two important effects, which influence the diffusion process.

First, the adoption process is influenced by the installed base, which is equivalent to the described Bass diffusion model. But the utility for each user is contrary to conventional goods not a constant value. According to the formula it grows exponentially with an increasing amount of actual users. This leads to the fact, that the diffusion process grows exponentially, too. This is called the “bandwagon effect”. To explain this metaphor, imagine that people follow a bandwagon attracted by the music. The higher the number of people following the bandwagon, the more are decoyed, too (Leibenstein 1950). This leads to a reinforcing process. Although this effect occurs with conventional products as well (“word-of-mouth” effect; Sterman 2000), in case of products influenced by network externalities the bandwagon effect is much stronger. Because of the exponentially growing utility the impact of the bandwagon effect on the diffusion process is higher. The exponential growth acts like a amplifier of the bandwagon’s music.

Second, the adoption process is determined by the number of users. Contrary to conventional products, in the beginning, products influenced by a direct network externality have no original utility. To establish a new network the utility must be created by the utilization of the users. The problem to establish a new network is that early users cannot derive enough benefit from the network. They enter the network hoping that other users will follow, thus their utility depends on the future decision of other potential users. This leads to a hesitating behavior of all potential users resulting in a imaginary barrier to enter the network based on the existing risk to back the wrong horse. Farrell and Saloner call this the penguin effect: “Penguins who must enter the water to find food often delay doing so because they fear the presence of predators. Each would prefer some other penguin to test the waters first” (Farrell and Saloner 1986, p. 943).

Finally, there is a important difference to conventional products concerning the utilization. The decision to buy a conventional product is the final element of the decision process. Contrary to that, the adoption process is not finished with the decision to buy a network product. The following utilization of the network product is important for the diffusion process as well. If the expected utility cannot be achieved, users can decide to discontinue their utilization, which leads to a decrease of the entire network utility. This may induce other users to stop their utilization and so on. This intensifies the penguin effect, because on one hand, potential users do not know if enough further users will follow, and on the other hand, they do not know if early users, which have already entered the network, will not leave the network disappointed.

In the following, all those effects will be successively integrated in a model. The diffusion of products showing network externalities is characterized by balancing and reinforcing feedback loops. This means that we can observe factors that influence this process positively and others that retard it. It is difficult to examine both effects simultaneously. Therefore, an “incremental” model building process of a system dynamics model is chosen. By adding more structure, simplifying assumptions are relaxed one after another. The corresponding behavior can then be analyzed. This approach can help to understand the relation between structure and behavior of the diffusion of products showing positive demand externalities.

Incremental Model Development to Understand Network Externalities

The following series of figures depicts the step-by-step refinement of a system dynamics model to cover the diffusion of products showing network externalities. The aim of this approach is to foster understanding of the investigated effects and concepts and to provide a model-based guideline for empirical research in later stages of this research project.

Figure 2 shows—similar to Figure 1 above—the fundamental Bass diffusion model. Sterman's (2000) interpretation of parameter β is included. The innovator feedback loop, however, is not elaborated because it is not in the center of interest in the context of this paper. Nevertheless, it must be noted that diffusion in early stages of the product life cycle is induced by innovators (and thus parameter α). The diffusion process cannot start without innovators (i. e., people not influenced by other users) which buy the product.

Variable names of the two levels are adjusted to the terminology in use when discussing network externalities. Note that, although two levels are depicted in the model, the levels are interdependent and the model therefore is a first-order system. The behavior graph shows a "prototypical" diffusion process with default values of parameters. After a certain point in time $\underline{t}$, all potential users have bought the product, i. e. $B_{\underline{t}} = P_0$.[2]

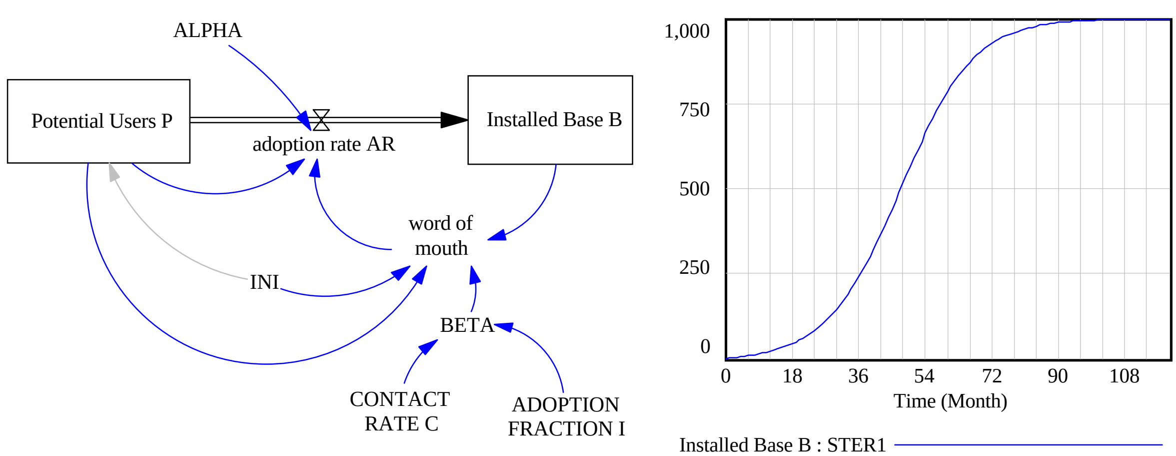

Figure 2: Classical Bass diffusion, modified after Sterman (2000)

The first extension of the model (Figure 3) incorporates the calculation of a utility variable, without implementing any additional feedback loops. To express utility we implement a dimensionless variable *average utility per user*, which is normalized to values between 0 and 1. The average utility per user depends on the possible number of interconnections (dependent on the number of users) and the fraction which determines how many of these interconnections are valuable for the individual:

*average utility per user = (Installed Base B-1)/2 * Relevant Adopter Fraction* and

*utility = Average utility per user * Installed Base B.*

To simplify things, we assume interconnections between two users of the product only. The behavior graph of *average utility per user* mimics the number of adopters. The process of diffusion itself shows the same behavior as above because no other structural or numerical changes are made.

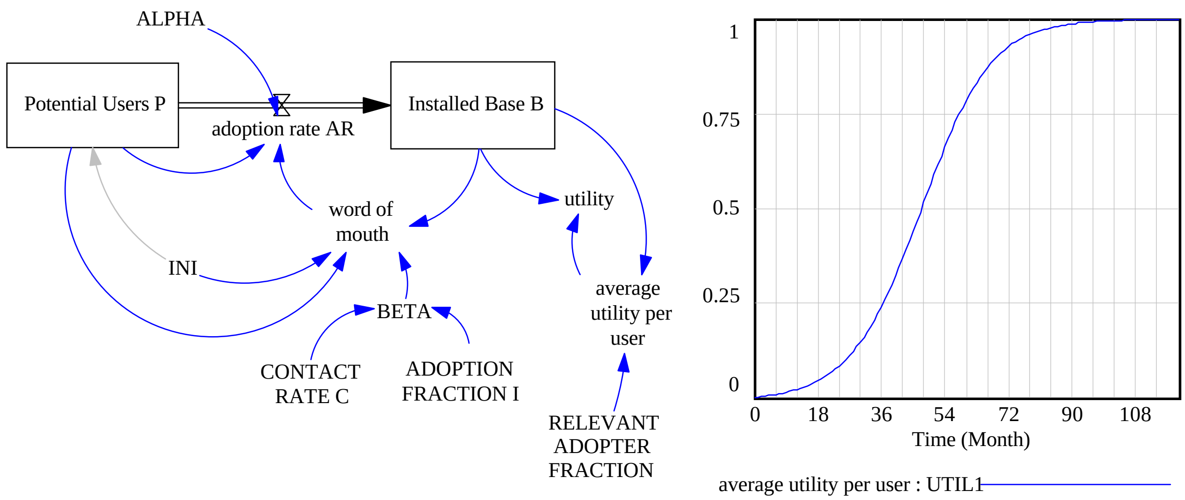

Figure 3: Diffusion including the calculation of utility

In the model depicted in Figure 4 we close the feedback loop between utility and adoption. Therefore, *average utility per user* now influences the fraction of individuals who become buyers of the product after being in contact with a user. As the simplest assumption we set:

adoption fraction i = average utility per user.

Everything else equal to the model setting in Figures 2 and 3, the proceeding of diffusion can be compared in the behavior graph. END_I is the simulation run with this model, UTIL1L the simulation run from above (just prolonged to 180 periods). It can be stated that diffusion needs longer to take off, but showing a steeper proceeding of *Installed Base B* in later periods. This behavior can be verified comparing the adoption rates of the two runs: although adoption starts later with an endogenously generated adoption fraction, it nevertheless has a higher amplitude. This behavior can be interpreted as penguin and bandwagon effect.

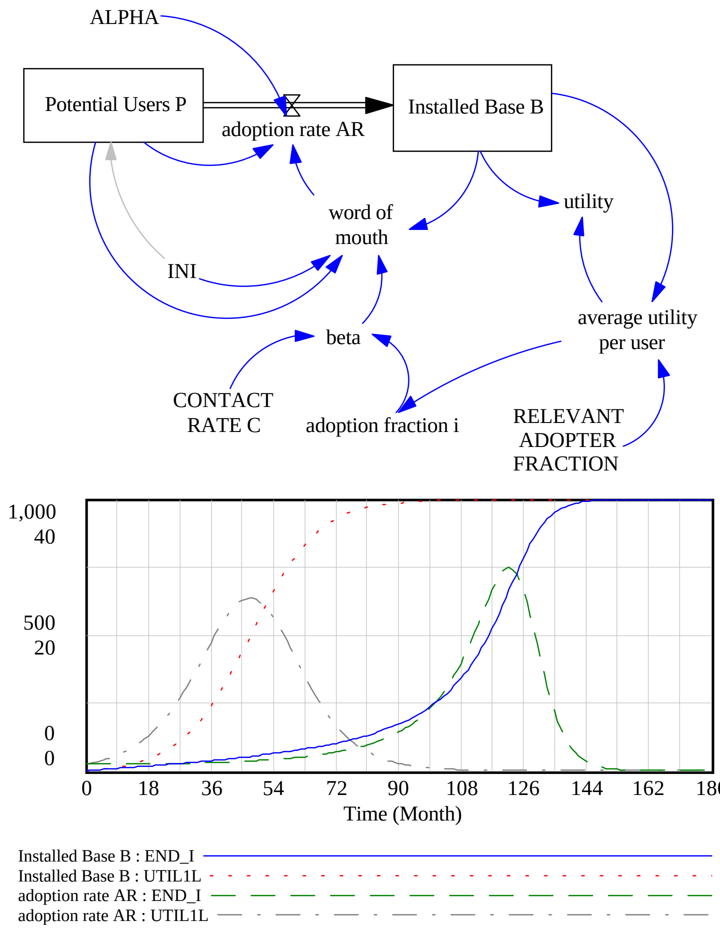

Figure 4: Endogenously calculated adoption fraction (depending on average utility)

In the next step, we relax the assumption that adoption fraction equals utility. We now assume that the fraction of people who adopt is dependent on a comparison between *average utility per user* and *DESIRED UTILITY*. If actual utility is bigger than the desired utility all individuals in contact with users adopt and buy the product. If it is smaller, however, only a fraction adopts. The size of this fraction depends on the distance between actual and desired utility and on the risk individuals are willing to accept:

IF THEN ELSE(average utility per user>=DESIRED UTILITY, 1 , T risk graph(average utility per user/DESIRED UTILITY)).

Figure 5 shows the graph function used for risk-friendly individuals. This means that even when the distance between *average utility per user* and *DESIRED UTILITY* is rather big, still relatively many individuals adopt in the hope of future improvements of the situation.

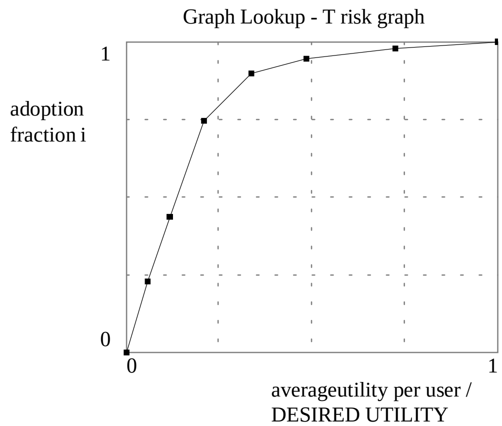

Figure 5: Graph Lookup of risk willingness of risk-friendly individual

With the help of such a risk graph we obtain the model depicted in Figure 6. In the behavior graph the simulation run of this model is compared to the run obtained with the basic model above. Again, we observe a later start of diffusion but a steeper advance.

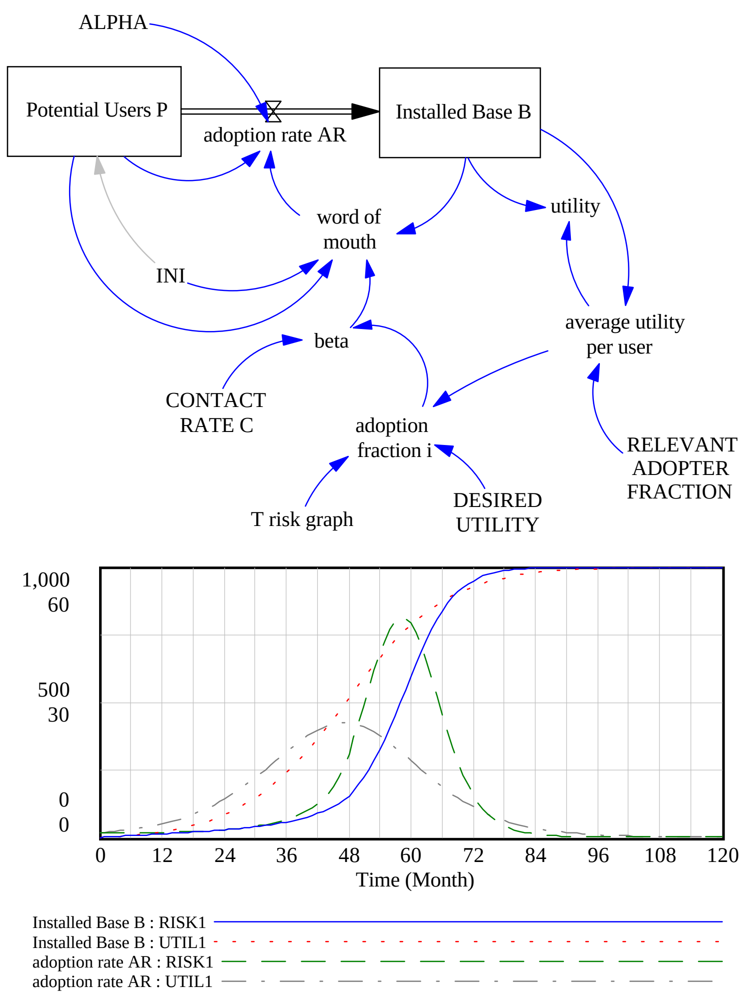

Figure 6: Risk function to compare average and desired utility

In Figure 7 the last step of model refinement covered in this paper is displayed. We now take into account that also some users of the installed base discontinue the usage because they are disappointed from the utility of the product. We modeled it in a way that again desired and actual utility are compared. The *discontinuation rate DR* is smoothed over a *PATIENCE* parameter which expresses the time that users are willing to wait for their situation to improve:

discontinuation fraction d = IF THEN ELSE(average utility per user>=DESIRED UTILITY, 0 , 1-(average utility per user/DESIRED UTILITY))

*discontinuation rate DR = discontinuation fraction d*Installed Base B/PATIENCE.*

Compared to the behavior of the model depicted in Figure 6 we can observe a delayed diffusion take off. Furthermore, this is the first version of the model in which *Installed Base B* does not reach its maximum value, the initial value of *Potential Users P*.

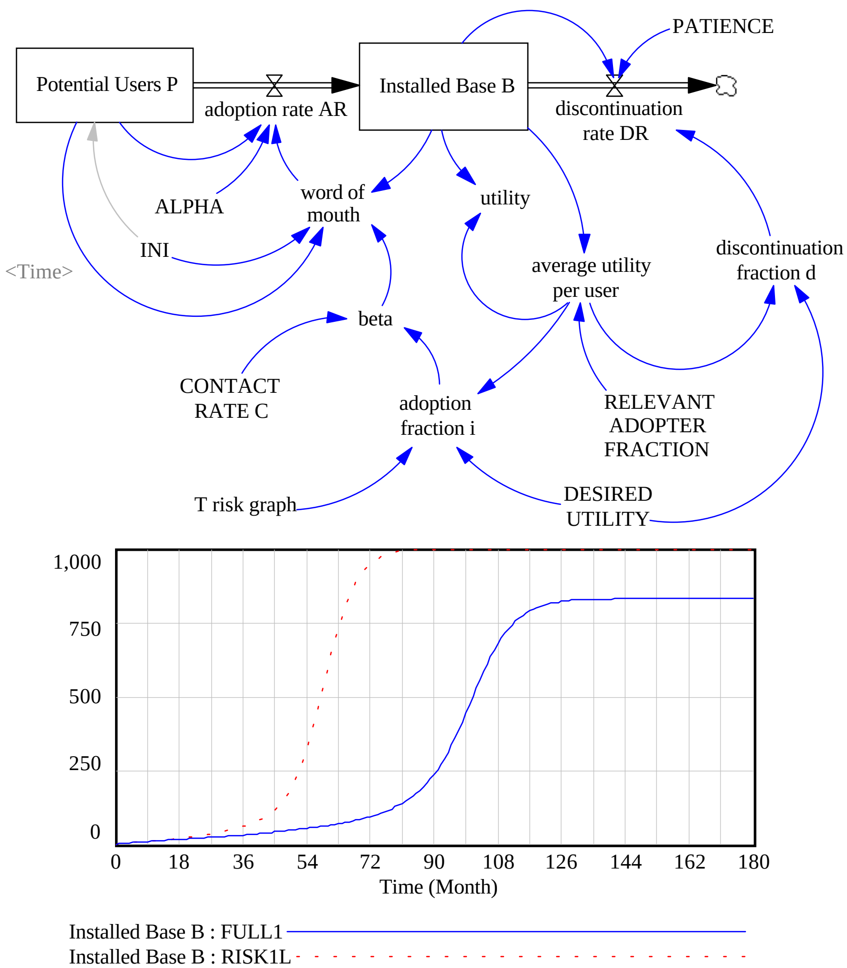

Figure 7: Full model with discontinuing users

Leverage Points for Managing Network Externalities

A few possible points to influence the behavior of the system can be identified immediately. As a first try, we discuss three leverage points to extend the installed base in the model as depicted in Figure 7 that seem quite promising:

1. patience of users within the installed base (*PATIENCE*),
2. willingness of potential users to take risks (*T risk graph*), and
3. desired utility of users (*DESIRED UTLITY*).

Before discussing if and how management can influence these factors, we should examine the effects of changes in these variables. Therefore, Figure 8 depicts behavior graphs of *Installed Base B* for different parameter settings. RISK1L is the reference mode from the model in Figure 6; FULL1 is the behavior already shown in the figure before. FULL2, FULL3 and FULL4 are simulation runs in which one of the variables *PATIENCE*, *DESIRED UTILITY* and *T risk graph* was manipulated. Behavior is nearly the same in all three cases: although the number of users in the installed base grows similar as in the base run FULL1, it nevertheless never reaches its full market potential and does not stay constant but erodes over time. FULL5 is a simulation run in which all three variables were manipulated simultaneously; in this case diffusion does not take off at all. The interpretation of this graph is straightforward: only if parameters in all these leverage points are tuned positively, a favorable behavior can be expected.

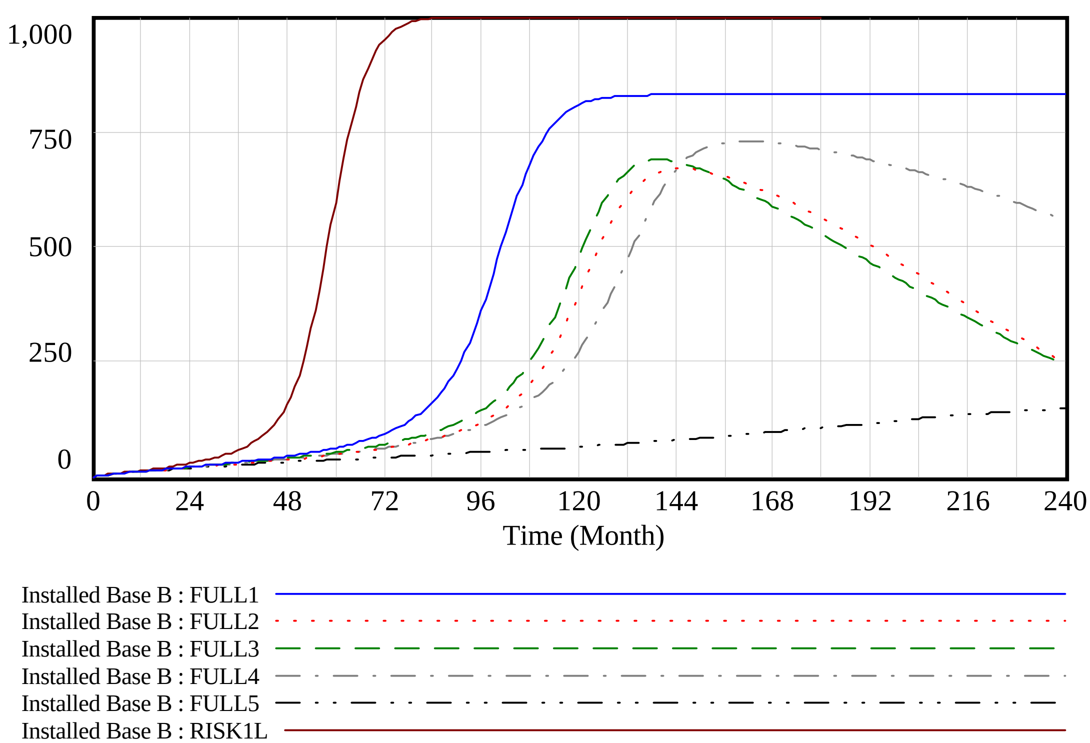

Figure 8: Installed base for different settings of variables in leverage points

However impressive the effects of changed parameters in these leverage points are, in reality management can only indirectly influence these variables. Patience of users within the installed base can probably be increased using marketing measures. Nevertheless, it must be assumed that users cannot be persuaded indefinitely to keep on using a product when it definitely lacks utility. In the same way, it seems hardly possible to change potential users' willingness to take a risk and invest in a product that shows only limited actual utility. Also, desired utility can be influenced only within a certain range. Thus, one conclusion is to manage all leverage points simultaneously because every single one is only of restricted effectiveness and responsiveness.

Another way to manage the diffusion process of products with network externalities is to increase the number of users as fast as possible. Our model suggests two ways how this could be achieved:

- Firstly, by putting more effort to activate innovators quickly. However, it can also be tried to let potential imitators become innovators, i. e. make them buy without having contact with other users before. In this case, their purchase is not based on the word-of-mouth effect but on advertising of the firm. In reality, however, it might be difficult to achieve this. Furthermore, as the simulation results in Figure 9 suggest, a higher *ALPHA* coefficient can boost adoption in the beginning but does not secure lasting success (simulation run LEV1). Note that in Figure 9 all parameters are set to (unfavorable) default values that lead to behavior as indicated in simulation run FULL5, i. e. no diffusion take off.
- Secondly, by increasing the *CONTACT RATE C* between non-users and users which can convince non-users to adopt. Again, our model suggests that this only works in the beginning of the product life cycle but does not yield lasting success (run LEV2).

Obviously, both strategies do not create lasting success. For a constant installed base to occur, one has to look for variables within the reinforcing feedback loop which generate the word-of-mouth effect. Besides *average utility per user*, the only parameter we have not discussed so far is *RELEVANT ADOPTER FRACTION*. This variable symbolizes to what extend users are interested in the theoretically possible communication relations. For instance, for an e-mail user not all other users of e-mail are interesting as communication partners. In the model, the effect is that—when increasing the relevant adopter fraction—the actual / desired utility ratio goes up, which again increases adoption and hinders discontinuation of users. The utility of the product is improved without the need of extending the installed base. If *RELEVANT ADOPTER FRACTION* can be increased by 50 % (0.002 to 0.003) the product diffuses and a constant installed base can be maintained (run LEV3) even with unfavorable settings of the other parameters.

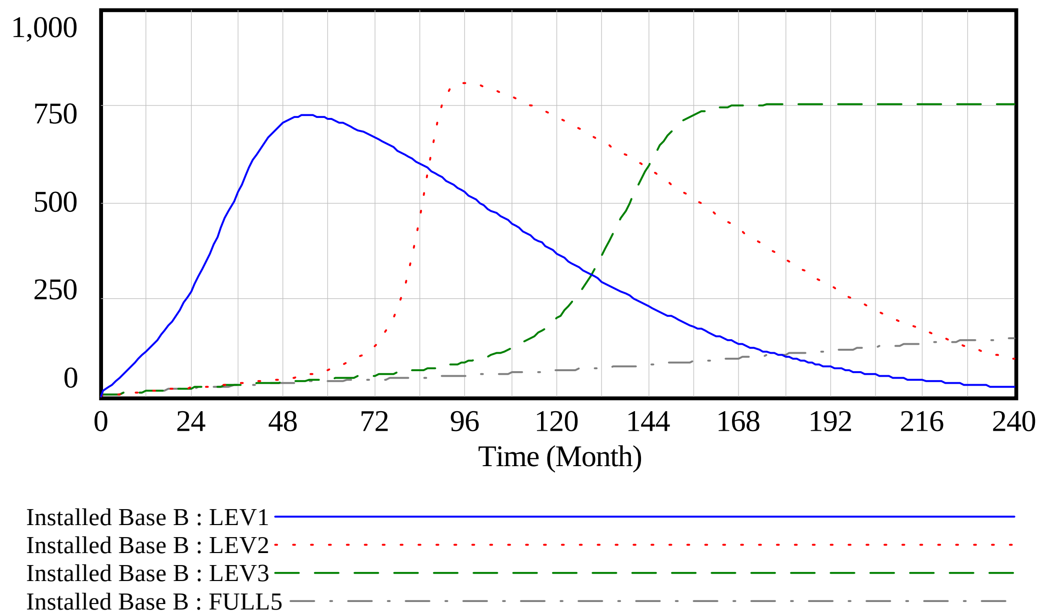

Figure 9: Other ways to influence the diffusion process

The management of the diffusion of products with network externalities should therefore focus on augmenting the pool of interesting communication partners of every user in the installed base. Ways to achieve this are

- marketing measures to make users communicate more with each other and also with formerly unknown people (e. g., “communities”),
- technical advances that make it possible to use a network product in new ways. This would primarily increase the utility of the product but—in a next step—could also make users communicate with new people (e. g., “SMS”). Furthermore, communication with more than one partner could be made possible (e. g., “conferencing”), and
- extending the installed base indirectly by creating compatibility to other products.

Further Research

The system dynamics model described in this paper is to a great extend preliminary. It was built to help understanding the nature of network effects and prepare further, also empirical research. Many opportunities for improvement of the model exist:

- Another way of taking advantage of the reinforcing feedback loop is to increase *average utility per user* directly. One chance of doing this is to improve the properties of the product in such a way that not only communication relations between two but also between more users are possible.
- It should be taken into account that potential users make their decision not only based on the comparison of actual and desired utility but to a great amount on expectations of future utility. The same holds true for the discontinuation of usage. Sterman’s (1987) TREND function could be used for this purpose.

- The reinforcing effects of complementary goods should be included. In this way, the focus could also shift to modeling the diffusion of products with indirect network externalities.
- The competition of two systems for the same stock of potential users could be investigated. Under what circumstances does one product succeed over the other?
- The number of potential users can change dynamically due to economic, demographic or other factors.
- Some customers can stop using a product but continue their usage later when utility satisfies their needs.
- Some of the individuals in the customer base could be more active in communicating the advantages of the product than others. Thus, the customer base needs differentiation.
- The patience factor of users in the installed base could be modeled more elaborately using a coflow structure.

Some of these extensions can hopefully be presented in our talk at the system dynamics conference.

References

Bass, F.M. (1969). A New Product Growth Model for Consumer Durables. *Management Science* 15(5), 215–227.

Bass, F.M. (1980). The Relationship between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations. *Journal of Business* 53(3), S51–S67.

Bental, B. and Spiegel, M. (1995). Network Competition, Product Quality, and Market Coverage in the presence of network externalities. *Journal of Industrial Economics* 43(2), 197–208.

Brynjolfsson, E. and Kemerer, C.F. (1996). Network Externalities in Microcomputer Software: An Econometric Analysis of the Spreadsheet Market. *Management Science* 42(12), 1627–1647.

Church, J. and Gandal, N. (1993). Complementary network externalities and technological adoption. *International Journal of Industrial Organization* 11, 239–260.

—. (1996). Strategic entry deterrence: Complementary products as installed base. *European Journal of Political Economy* 12, 331-354.

Farrell, J. and Saloner, G. (1986). Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation. *American Economic Review* 76(5), 940–955.

Kalish, S. and Lilien, G.L. (1986). Applications of Innovation Diffusion Models in Marketing. In Mahajan, V. and Wind, Y. (eds.), *Innovation Diffusion Models of New Product Acceptance*, Ballinger, Cambridge, MA.

Katz, M.L. and Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *American Economic Review* 75(3), 424–440.

Katz, M.L. and Shapiro, C. (1992). Product Introduction with Network Externalities. *Journal of Industrial Economics* 40(1), 55–83.

Leibenstein, H. (1950). Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand. *Quarterly Journal of Economics* 64(2), 183–207.

Mahajan, V. and Peterson, R.A. (1985). *Models of Innovation Diffusion*, Sage, Beverly Hills/London/New Delhi.

Maier, F.H. (1995). *Die Integration wissens- und modellbasierter Konzepte zur Entscheidungsunterstützung im Innovationsmanagement*, Duncker & Humblot, Berlin.

—. (1998). New Product Diffusion Models for Decision Support in Innovation Management. *System Dynamics Review* 14(4), 285–308.

Milling, P.M. (1996). Modeling Innovation Processes for Decision Support and Management Simulation. *System Dynamics Review* 12(3), 211–234.

Rogers, E. (1983). *Diffusion of innovations*, 3rd edition, Free Press, New York/London.

Sterman, J.D. (1987). Expectation Formation in Behavioral Simulation Models. *Behavioral Science* 32, 190–211.

—. (2000). *Business Dynamics*, Irwin McGraw-Hill, Boston, MA et al.

Xie, J. and Sirbu, M. (1995). Price Competition and Compatibility in the Presence of Positive Demand Externalities. *Management Science* 41(5), 909–926.

Notes

1. Equations of this and the following models are available from the authors on request.
2. Technically, the curve for installed base asymptotically approaches the initial number of potential users but never really reaches it.