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Dynamics of R&D and Innovation Diffusion

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Abstract

The article describes a comprehensive approach to model the processes of research and development, the introduction of new products, i.e. the stage of innovation, and the process of diffusion of new products in the market place. It emphasizes the importance of an integrated view of the different stages of innovation processes. The aim is to generate insight in the complexity and the dynamics of innovation processes. After a brief discussion of modules to map R&D and innovation diffusion for different market conditions, a model which links the three stages of the innovation processes together is described and analyzed. Since the model views innovation processes from the perspective of the management of a firm, it shows the influence of corporate decision variables like pricing, R&D-budgeting or quality control on the diffusion of innovations and the development of firms.

1. Importance of Permanent Innovation Activity

Incessant activities of improving and renewing a company's range of products and its production processes are commonly seen as crucial for survival in a competitive environment. However, to improve a company's competitive position or to increase its competitive advantage, ongoing innovation activity through the development, test and introduction of new products and/or production processes is necessary. This simplified description of the major tasks and objectives during the process of R&D, innovation, and diffusion is faced with highly dynamic and complex problems that have to be solved during the innovation processes by management. During recent years it could be observed that new and technically more complex and sophisticated products and processes have to be developed in a shorter span of time. Resources have to be allocated to research and development projects that are expected to be economically successful. New products have to be introduced to global markets with stiff competition. Decisions about the adequate time to market and appropriate pricing, advertising, and quality strategies have to be made.

The complexity and difficulties to manage innovation activities partly derive from the comprehensiveness of the innovation processes. According to Schumpeter (1961) innovation processes can be separated in three stages: (1) invention, the phase where new products are developed, (2) innovation, i.e. the phase of introducing new products in the market, and (3) imitation or diffusion, the spreading of new products in the market place (see Figure 1). To be and to remain competitive, companies have to be successful in all stages of the innovation process. This becomes obvious when empirically derived new product failure rates and innovation costs are analyzed. Figure 1 illustrates the cascading process of innovation activity and the related innovation costs. Only approximately 40% of all research projects can be seen as successful from a technical point of view. 22% of all R&D projects lead to products that are introduced to the market and 18% are stopped because of the missing economic potential in the market place. Considering the 22% that are introduced in the markets, only 40% of these are economically successful. This means that only 8.8% of all R&D projects turn into economic successes (Mansfield et al. 1981)[1].

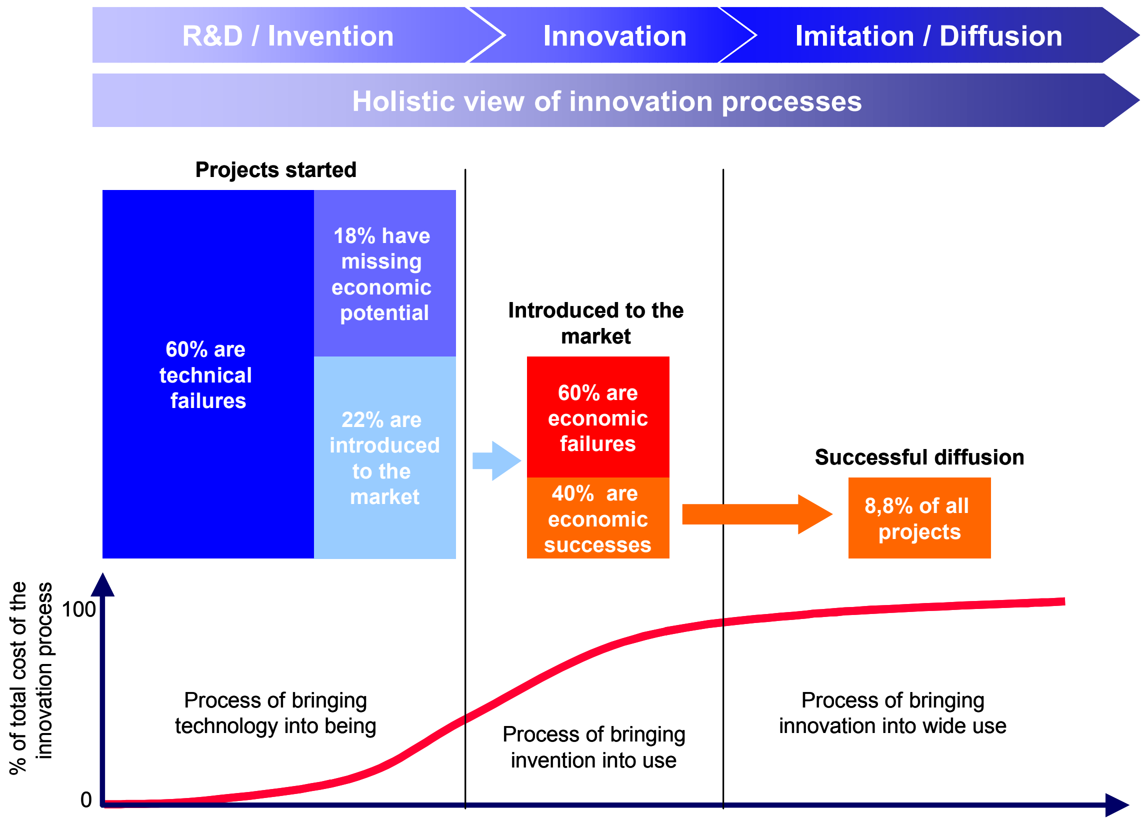


Figure 1: Outcome of innovation activities

These numbers gain even more importance, if the costs of innovation activities are considered. All stages in the process of innovation require resources that have to be used efficiently if a company wants to stay competitive in the long run. The total cost of innovation during the stage of R&D add up to around 50% of the total innovation cost[2] and are caused by 78% by R&D projects which become either a technical failure or which are stopped because of insufficient economic potential. The other approximately 50% of the total cost of innovation activities are caused by investments in new product introductions, e.g., for the setup of new production facilities, advertisement campaigns etc. In consequence, the 8.8% of all R&D projects that can be seen as market successes have to earn all necessary resources. This shows the importance each phase of the innovation process has and the necessity of a competent management in these stages. But this requires the understanding of the complexity and the dynamics within and over all stages of the process of innovation.

Many concepts to support the management of innovation only consider the distinct and separated stages. From a system dynamics perspective, the modeling of R&D processes has a long tradition. Roberts (1964, 1978a, 1978b) and Weil et al. (1978) used the System Dynamics approach to investigate the dynamics of R&D projects in search for levers for an effective management of R&D projects. Ford and Sterman (1998) investigate the dynamics of new product development projects and the interactions between the different stages and tasks of these projects. Several basic research articles discuss different approaches to model the diffusion of innovations over time. They form a methodological basis for a variety of models of innovation diffusion, but concentrate on the stages of innovation and diffusion of a new product in a market. The perspective of this article is different. Although it will briefly examine these models and show that they are insufficient to improve the understanding of the structures and forces driving the processes of R&D, innovation and diffusion, its main focus are the interactions between the three Schumpeterian stages of the innovation process. Based on the general framework of innovation diffusion for monopolistic markets described by Milling (1986a, 1996) the article shows, how the System Dynamics perspective contributes to the understanding and management of innovation processes.

Figure 2 shows in a feedback diagram the influences of corporate decision variables (marked with hexagons) like pricing, advertising, capacity allocation for production and quality control, and investments in capacity and R&D, on technical capability of the products and on demand. It also shows how corporate decisions are interconnected through several feedback structures. Although the interpretation of the figure is limited to a simple market structure and does by far show not all potential feedback relations, it gives an impression of the complexity of a comprehensive innovation process model.

Decision variables like pricing or advertising show a direct impact on the probability of a purchase. The higher the advertising budgets and the lower the price, the higher will be demand for the products of a company. There are also indirect or delayed effects, which slow down or speed up the spread of a new product in the market. The actual sales of a product may be limited by insufficient production and inventory, which increase the delivery delays perceived by the potential customers and therefore result in decreasing probability of demand and purchase. Growing demand motivates the company to expand its capacity and to increase the volume of production. This leads to higher cumulated production and through experience curve effects to decreasing costs per unit, lower prices, and therefore to still further increased demand (Milling 1996).

Since the total capacity has to be used partly to ensure the quality of the output, a certain percentage of capacity has to be allocated to quality control—either end of pipe or during the production process. Quality control will improve product quality, which directly affects demand.

The interactions between markets and functional areas of a company are highly dynamic. For an improved understanding of the feedback structures that drive innovation processes an approach is needed, which considers these aspects. The System Dynamics approach is highly suitable for these kinds of problems. A model developed in this manner can serve as a simulator to analyze the consequences of different strategies and to improve understanding of innovation dynamics. It can show e.g., how R&D strategies, pricing strategies, and investment strategies influence each other. It can also show the impact of intensified quality control on production and sales of a period (Milling 1986b, Milling 1987, Milling 1989, Milling 1996), and therefore can be used to investigate the effects resulting from the links between, R&D and other functional areas as well as the markets of a company.

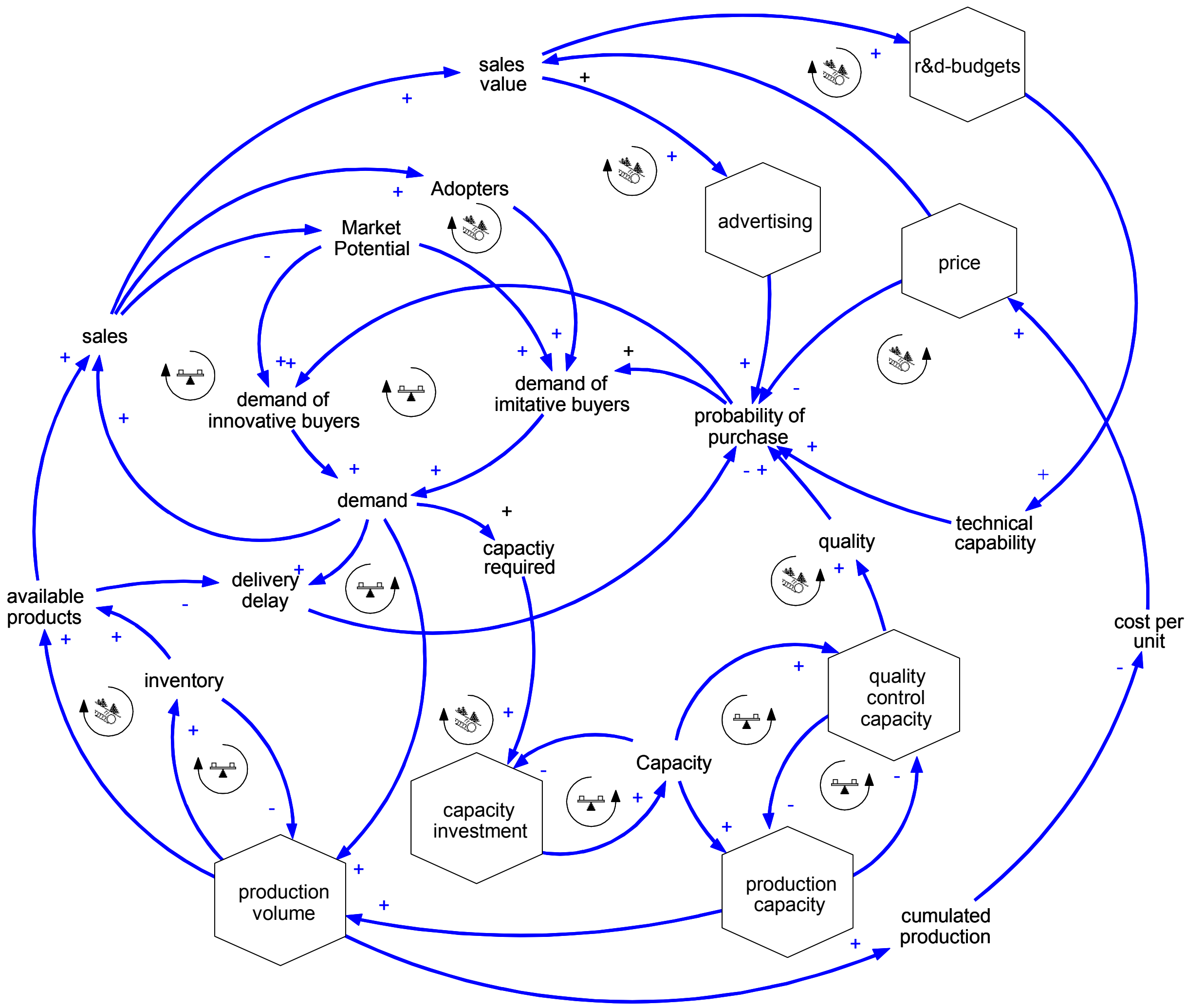


Figure 2: Feedback structures driving innovation processes

2. A System Dynamics Perspective of R&D and Innovation Diffusion Models

The numerous interactions between the different stages of the innovation process require a comprehensive approach. Models, which do not consider these interactions, must fail if they are used as a tool to evaluate strategies or to generate an improved understanding of innovation processes. This chapter outlines how the different stages can be modeled and which specific aspects have to be considered. Therefore, in a first step an evolutionary algorithm will be discussed to model the research and development stage. A second step discusses different approaches to model the stages of innovation diffusion of a new product or a technological innovation in the market. The third step finally links the models of research and development and innovation diffusion under competitive conditions.

2.1. Modeling R&D Processes

The stage of research and development deals largely with intangible and at least partly stochastic processes. The uncertain outcome of industrial R&D is commonly observed. In literature many attempts are described to define a production function for research and development similar to that of material goods. These R&D production functions use as input the resources allocated like budget, number of people assigned or laboratory equipment available. As output for example the number of innovations or patents are used. These approaches to model R&D processes fail for several reasons. First, R&D is highly stochastic, and the input-output relation mapping the R&D production function must also be stochastic. Second, the output is extremely heterogeneous, which leads to measurement problems (see Schröder 1973 for a discussion of production functions for R&D). Additionally, these models are black box approaches; they are not successful in describing how the various factors influencing the outcome of this stage operate together and are not suitable to generate insights in the development of technological innovations over time. Here a different approach is suggested. Since the development of new knowledge can be seen as an evolutionary process, an analogy to biological evolution theory defines how new concepts develop by the variation and mutation of existing and known solutions. The results are evaluated on the basis of their viability. If they seem to be superior to previous combinations, they are selected for further development, and hence for future evolution; otherwise they are discarded (see Milling and Maier 1996 for a comprehensive description). Technological knowledge of a company and a product is modeled as binary matrices with the entries "1" and "0" (Figure 3).

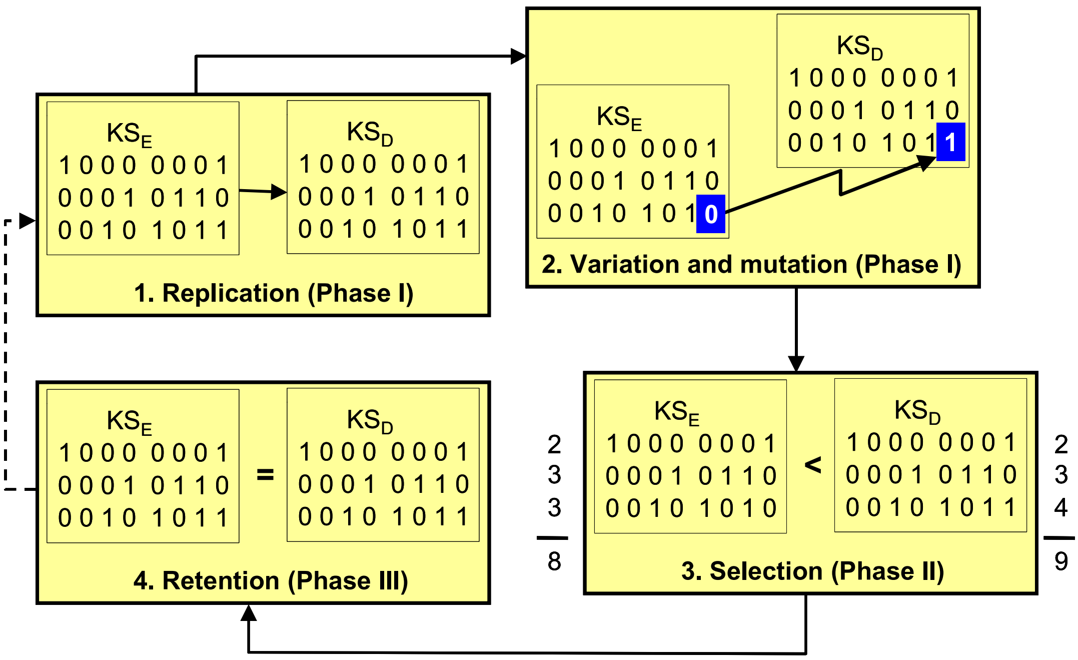


Figure 3: Evolutionary approach to R&D

Each matrix can be interpreted as a basic invention that gives access to the potential of a new technology. The size of the matrix represents the maximum technological potential and expresses the importance of a technology. The element "0" is interpreted as basic knowledge in the field of the technology; the element "1" means applied knowledge which then will be incorporated in a new product. For programming reasons—one byte represents a single row—, the number of columns is limited to 8; whereas the number of rows is only limited by technical restrictions of the computer system used to run the model. Currently matrices with 1250 to 8000 rows are used. The value of a matrix—and therefore the worth of the technical know-how—is determined by counting the number of elements with the value "1". It determines the units of technical know-how incorporated in a product. The difference between the maximum possible number of elements which could have the value "1" and the actual number characterizes the technological potential.

Figure 3 describes the evolutionary process that is used to map the R&D process. The evolution algorithm—it is written in the programming language C and can be linked to a Vensim-based system dynamics model—follows three phases of evolution. In a first step of phase I (replication) the matrix of a technology, i.e., the knowledge system elder (KS_E) is duplicated to the knowledge system descendant (KS_D). In the second step of phase I (variation and mutation) the algorithm randomly selects an element of the matrix (KS_D) and changes the value of the element from “0” to “1” and vice versa.

In phase II selection takes place. The value of the matrix (KS_D) is compared to the value of the knowledge system (KS_E) by counting the number of elements with the value “1” (selection). If the value of (KS_D) is higher—as in the example of Figure 3—, the new matrix is selected; otherwise, it is rejected. Phase III (retention) then realizes the result of the selection. The technological system with the higher number of elements with the value "1" is the superior one and becomes the basis for the next evolutionary step, i.e. the knowledge system (KS_D). The number of variations and mutations of the matrix in each period of time depends on the intensity and the volume of the R&D process (Milling and Maier 1996). This analogy to biological evolution theory defines how new concepts develop by the variation and mutation of existing and known solutions and the following selection. The respective results are evaluated on the basis of viability. If they are superior to previous combinations, they are selected for further development and become the basis for future evolution; otherwise they are discarded.

The evolutionary algorithm described above generates the time behavior shown in Figure 4. The left part shows the evolution of the technological knowledge for four succeeding technologies of a company, i.e. the worth of the four technology matrices. The right part shows the time behavior of the rate of success of R&D and the remaining technological potential as a percentage of the total potential knowledge of a technology. The number of evolutionary steps during each period of time depends on the intensity and the volume of R&D, which is set to be constant during the simulations. In reality it is influenced by the resources a company allocates to R&D. Hence, resources allocated to the process drive the outcome of research and development. Nevertheless, the behavior is influenced by stochastic elements since the outcome of variation and mutation depends on the random number picks of the elements of the binary elements of the knowledge matrices.

The evolutionary approach using binary matrices to map the process of generating new knowledge can also be seen in a stock-flow perspective (Figure 5). The number of rows and columns determine the technological potential that is increased by basic research results. This corresponds to the addition of new rows to the binary matrices in the evolutionary algorithm. The technological potential is decreased by inventions made during the process of R&D. In the evolutionary algorithm this corresponds to the successful variation of an element with the value “0” into an element with the value “1”. The inventions itself increase the amount of technological knowledge.

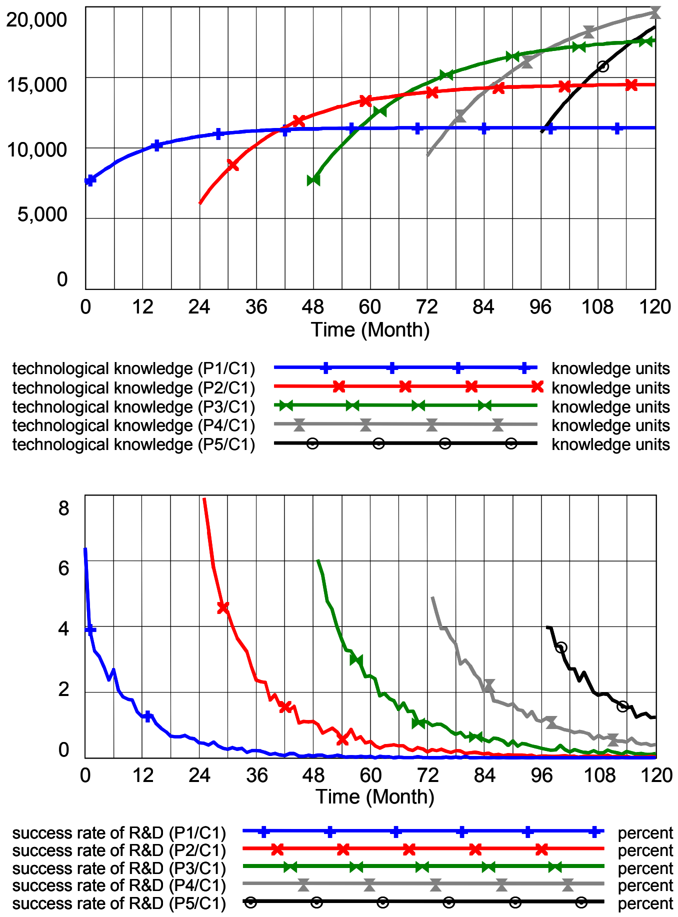


Figure 4: Behavior over time of the evolutionary R&D processes

In both, the evolutionary algorithm and the simple stock-flow structure, the technological knowledge will be incorporated into new products. Once the technological knowledge is incorporated into a new product and if the new product is introduced into the market the technological knowledge becomes applied technical knowledge. The new product is ready for market introduction, if the technological knowledge exceeds a required value. Here, the stages of innovation and diffusion come into play. The market introduction of a new product initiates the phase of innovation and starts the diffusion process. The more successful the product is in the market place, the more resources are generated for allocation to research and development. This links the R&D process to the market cycles of new products. The following chapter will discuss several approaches to model these market cycles, the processes of innovation diffusion.

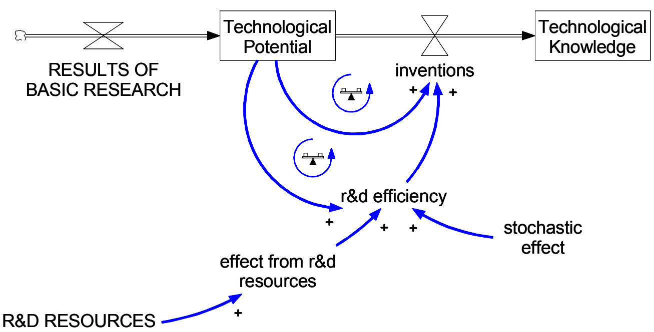


Figure 5: Structure of the R&D process model as stock-flow-diagram

2.2. Innovation Diffusion Models

The product life cycle concept is a key framework in business management. It describes the time pattern a product follows through subsequent stages of introduction, growth, maturity, and decline. Although the concept is a powerful heuristic, many models generating the typical behavior over time do not reflect properly the factors causing it. They are based on biological or physical analogies and do not consider e.g., actual economic environment, competition, capital investment, cost and price effects. A comprehensive discussion of basic methodological differences between these perspectives is provided by Georgescu-Roegen (1971). Purchasing decisions do not follow the same natural laws as the spread of a disease or the dissipation of particles. Nevertheless, several innovation diffusion models discussed in literature do not comprise the relevant decision variables. These models exhibit a significant lack of policy content. They do not explain how structure conditions behavior. They cannot indicate, how actions of a firm can promote and also impede innovation diffusion and adoption.

Besides the decision variables of a company, the aspects of market structure—monopolistic, industry level or competitive—and substitution through successive product generations are important structural elements that have to be considered. These aspects serve as a guideline for the next chapters. In a first step a model will be discussed, that maps the diffusion of an innovation in a monopolistic situation or which can serve as an industry level innovation diffusion model. This is followed by the introduction of competition between potential and existing companies in the model. Substitution between successive product generations is then considered as the last step of the development of an innovation diffusion model. Each step adds complexity to the previous model. This stepwise approach allows a better understanding of forces that drive the spread of a new product in the market.

2.2.1. Monopolistic or Industry Diffusion Models

In the following, the coarse structure of a model generating the life cycle in the market of a new product is presented and analyzed in its dynamic implications. The model is designed and evaluated on the basis of following assumptions: First, production on stock is not considered. When incoming orders stay below capacity, the level of output is reduced accordingly. Secondly, the basic market acceptance of the innovation is assumed. The model serves as a simulator to determine how individual strategies can accelerate or hamper market penetration and profit performance. It is not designed to predict the basic market success or failure of innovations (Milling 1986a, 1986b, Milling 1991a, 1991b).

Figure 6 shows in an aggregated view the main structure of the model[3]. The diffusion of a new product is generated by the behavior of two different types of buyers: innovators and imitators. If the Potential Customers *(PC)*—i.e. the market potential of a product—decide to purchase, either as innovators or as imitators, they become Adopters *(ADOP)*. The variables *PC* and *ADOP* and their associated transfer rates are the basic variables of the core diffusion process. The Untapped Market *(UM)* covers latent demand that can be activated by appropriate actions and leads to an increase in the number of potential customers. Besides the growth resulting from the influx from the untapped market also a decline in market volume can be caused by the loss of potential customers to competitors. This Lost Demand *(LD)* turned to competing products that are more attractive, e.g. products of a higher level of technological sophistication, quality or lower price.

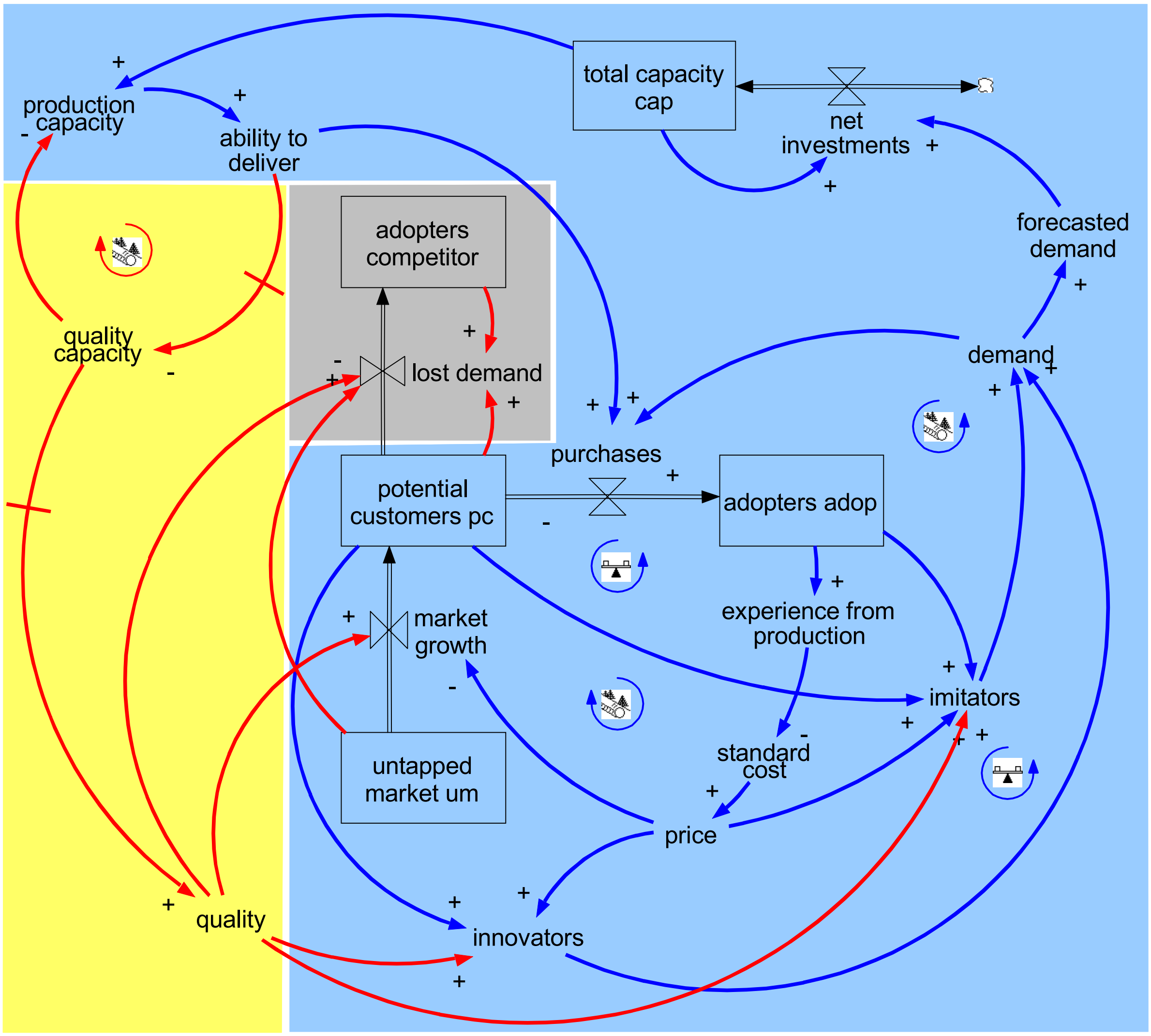


Figure 6: Coarse structure of the innovation diffusion model

The differentiation into the two buying categories “innovators” and “imitators” is frequently found in innovation literature (see e.g., Bass 1969, Rogers 1983). The distinction is made because these two types of buyers react differently to the market penetration already achieved, prices charged, or product quality offered.

The term “innovator” refers to customers who make their purchasing decision without being influenced by buyers who already purchased the product, the adopters. In the beginning of an innovation diffusion process, innovators take up the new product because they are interested in innovations. The number of innovators is a function of the Potential Customers (Bass 1980, 1969). Mathematically, the purchasing decision of innovators D^{Inno} is defined by an “innovation coefficient” α times the number of potential customers PC.

$$D_{(t)}^{Inno} = \alpha \cdot PC_{(t)} \tag{1}$$

with:

$D_{(t)}^{Inno}$	Demand from innovators
α	Coefficient of innovation
$PC_{(t)}$	Potential Customers

The purchasing decision of "Imitators" is derived differently. Imitators buy a new product because they observe or communicate with customers who have already adopted the good; they imitate the observed buying behavior. Innovators initiate new product growth, but it gains momentum from the communication between potential customers and the increasing level of adopters. This communication approach is based upon the concepts of diffusion theory, which was used in numerous scientific disciplines to develop formal models of diffusion (see e.g., Pearl 1924, Bailey 1957, Mahajan and Muller 1979).

To model this behavior, the number of possible contacts between the members of this set has to be determined (Milling 1986a). If *N* is the total number of people, the amount of possible combinations C_N^k between them is

$$C_N^k = \binom{N}{k} = \frac{N!}{k!(N-k)!} \tag{2}$$

Here we are only interested in paired combinations (k = 2) between the elements in *N*

$$\begin{aligned} C_N^2 &= \binom{N}{2} = \frac{N!}{2!(N-2)!} \\ &= \frac{N(N-1)}{2!} = \frac{1}{2}(N^2 - N) \end{aligned} \tag{3}$$

Since *N* represents the sum of elements in *PC* and in *ADOP, (N = PC + ADOP),* the number of combinations between potential customers and adopters is

$$\begin{aligned} &= \frac{1}{2}\left[(PC + ADOP)^2 - (PC + ADOP)\right] \\ &= \frac{1}{2}\left[PC^2 + 2 \cdot PC \cdot ADOP + ADOP^2 - PC - ADOP\right] \end{aligned} \tag{4}$$

and after regrouping and collecting terms we get

$$= \frac{1}{2}\Big(\underbrace{2 \cdot PC \cdot ADOP}_{\substack{\text{Communication between} \\ \text{PC and ADOP}}} + \underbrace{PC^2 - PC}_{\text{Communication within PC}} + \underbrace{ADOP^2 - ADOP}_{\text{Communication within ADOP}} \Big) \tag{5}$$

Internal communications, both within *PC* and *ADOP,* generate no incentive to purchase the new product and are neglected; the process of creating imitative buying decisions (6) is therefore reduced to the first term in (5), the information exchange between potential customers and adopters.

$$D_{(t)}^{Imit} = \beta \cdot PC_{(t)} \cdot ADOP_{(t)} \tag{6}$$

with:

$D_{(t)}^{Imit}$	Demand from imitators
β	Coefficient of imitation
$ADOP_{(t)}$	Adopters

The coefficient of imitation β represents the probability that the possible contacts between members in *PC* and *ADOP* have been established, relevant information has been exchanged and a purchasing decision is made.

The sum of the demand of innovators and imitators in each period, $D_{(t)}$, establishes the basic equation for the spread of a new product in the market. Together with the state variables of potential customers and adopters the flows of buyers (innovators and imitators) constitute the core model of innovation diffusion that generates the typical s-shaped pattern of an adoption process over time.

$$\begin{aligned} D_{(t)} &= D_{(t)}^{Inno} + D_{(t)}^{Imit} \\ &= \alpha \cdot PC_{(t)} + \beta \cdot PC_{(t)} \cdot ADOP_{(t)} \end{aligned} \tag{7}$$

Although the model explains the diffusion of an innovation as a process of communication and points out the importance of the different flows, it still lacks the crucial aspects and key variables of managerial decision-making. To be a useful tool for management corresponding extensions are a prerequisite. In a first step, the model is extended to generate dynamic cost behavior. Standard costs are the basis for the calculation of prices, which are an important decision variable. Experience curve effects are modeled based on cumulated production, in order to map the long-term behavior of standard cost. The actual costs of a product in a certain period are derived from the standard cost modified for variations resulting from capacity utilization.

The concept of experience curve effects (Boston Consulting Group 1972) suggests a direct relationship between cumulated production $X_{(t)}$ and average standard cost per unit $C_{(t)}^{s}$, adjusted for inflation; where C^{s} defines standard unit cost at the planned level of production. Every doubling of $X_{(t)}$ is associated with a cost reduction in real terms by a constant percentage according to:

$$C_{(t)}^{s} = C^{n} \left(\frac{X_{(t)}}{n} \right)^{-\delta} \tag{8}$$

where C^{n} stands for the cost of unit n $(n \subseteq X)$ and δ represents a constant which depends on the experience rate. For many businesses experience rates of 10 % to 20 % have been observed and ample empirical evidence for this relationship is available.

The costs of a product in each period of time $C_{(t)}$ are a function of cumulated production $X_{(t)}$ and capacity utilization determined by the production volume of a period $x_{(t)}$ as defined in (9). Figure 7 shows the behavior of the dynamic cost function

$$C_{(t)} = \Phi\left(X_{(t)}, x_{(t)}\right) \tag{9}.$$

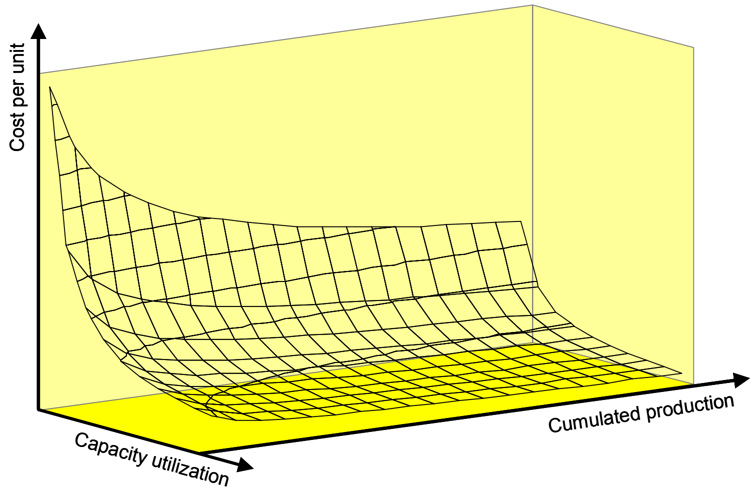


Figure 7: Dynamic cost function

Furthermore, the model is expanded through the elements of (i) market development, (ii) product pricing and its impact on operating results, and (iii) resource allocation, e.g., capital investment, production volume and quality control (see Milling 1986b, 1987, 1991a for more details). Figure 8 shows the run of a model version including market development. It concentrates on the structural linkages shaded at the right in Figure 6.

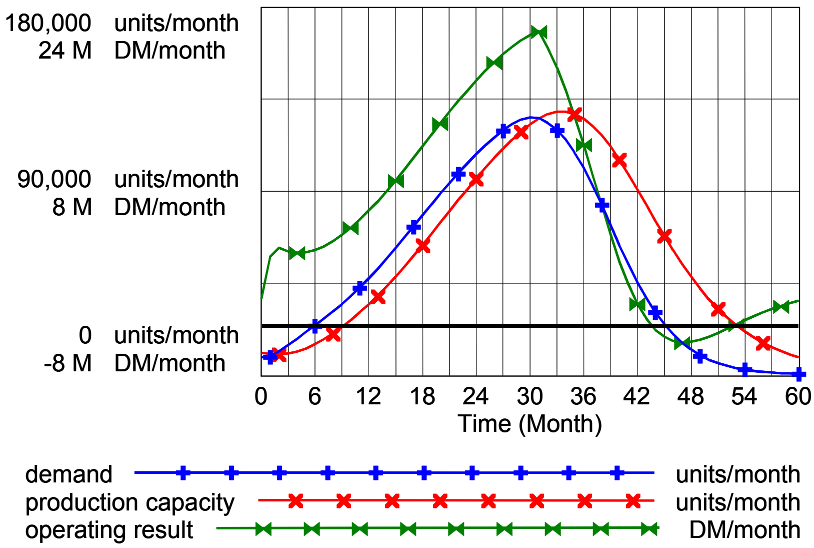


Figure 8: Reference mode of the monopolistic innovation diffusion model

The curves of production, demand, and operating results duplicate usual characteristics of the life cycle of a successful innovation. After the product launch additional customers can be gained from an untapped market as diffusion and thereby product awareness proceeds and prices decline. The maximum of demand from imitators—the quantitatively most important fraction of demand—is reached when the amount of possible communications between potential customers and adopters reaches its maximum. The decreasing level of potential customers and the depletion of the untapped market cause the decline towards the end of the simulation. The behavior also shows that demand rises much faster than the company can increase its production capacity. The behavior of Figure 8 will serve as reference mode for further analysis.

Pricing strategies and decisions are an additional important element to which the model is extended. The problem of the “right price” for a new product is essential but still unsolved in the area of innovation management. Difficulties to recommend the optimal pricing policy derive in particular from the dynamics in demand interrelations, cost development, potential competition, and the risk of substitution through more advanced products. Regardless of this complex framework several attempts in management science try to derive and to apply optimal pricing policies. However, they are faced with difficulties, both mathematical and practical. Their results (see e.g. Jeuland and Dolan 1982) are too complicated to support actual pricing decisions. Therefore simulation studies found more frequently their ways into management science.

The model is extended with four predefined pricing policies to investigate the impact of pricing decisions on market development on operating results (Milling 1986b):

- *Myopic profit maximization* assuming perfect information about cost and demand. The optimal price p^{opt} is derived from elasticity of demand $\varepsilon_{(t)}$ and per unit standard cost $c^{s}_{(t)}$ considering the impact of short term capacity utilization:

$$p^{opt}_{(t)} = c^{s}_{(t)} \cdot \frac{\varepsilon_t}{\varepsilon_t - 1} \tag{10}$$

- *Skimming price* strategy aims at serving innovative customers with high reservation prices and then subsequently reduces prices (Clarke and Dolan 1984). The model applies a simple decision rule modifying $p^{opt}_{(t)}$ through an exponential function that rises the price during the first periods after market introduction:

$$p^{skim}_{(t)} = p^{opt}_{(t)} \cdot \left(1 + a \cdot e^{\frac{-t}{T}} \right) \tag{11}$$

- *Full cost coverage,* i.e. standard cost per unit plus a profit margin π to assure prices above cost level even during the early stages of the life cycle:

$$p^{fcc}_{(t)} = c^{s}_{(t)} \cdot \pi \tag{12}$$

- *Penetration pricing* aims at rapidly reaching high production volumes to benefit from the experience curve and to increase the number of adopters. It uses a similar policy as for the skimming price but instead of a surcharge it decreases prices early after market introduction:

$$p^{pen}_{(t)} = c^{s}_{(t)} \cdot \pi \cdot \left(1 - a \cdot e^{\frac{-t}{T}} \right) \tag{13}$$

The simulation runs shown in Figure 9 give an overview of the development of profits, cumulated profits, and sales for the four pricing strategies discussed above. The model assumes that there is an inflow from the untapped market which depends on the dynamic development of prices, second, that there is no risk of competition and third, that repeat purchases do not occur. Taking profits into account, Figure 9 indicates that in a dynamic environment over the time horizon that is observed, the classic pricing rule for profit optimization leads to results that are superior to all other pricing strategies from a financial point of view. However, if judged by the market development the strategy of penetration prices is the appropriate strategy. This strategy allows rapid penetration of the market by setting relatively low prices, especially in the early stages of the life cycle. The combined price and diffusion effects stimulate demand and reduce the risk of loosing potential customers to upcoming substitution products.

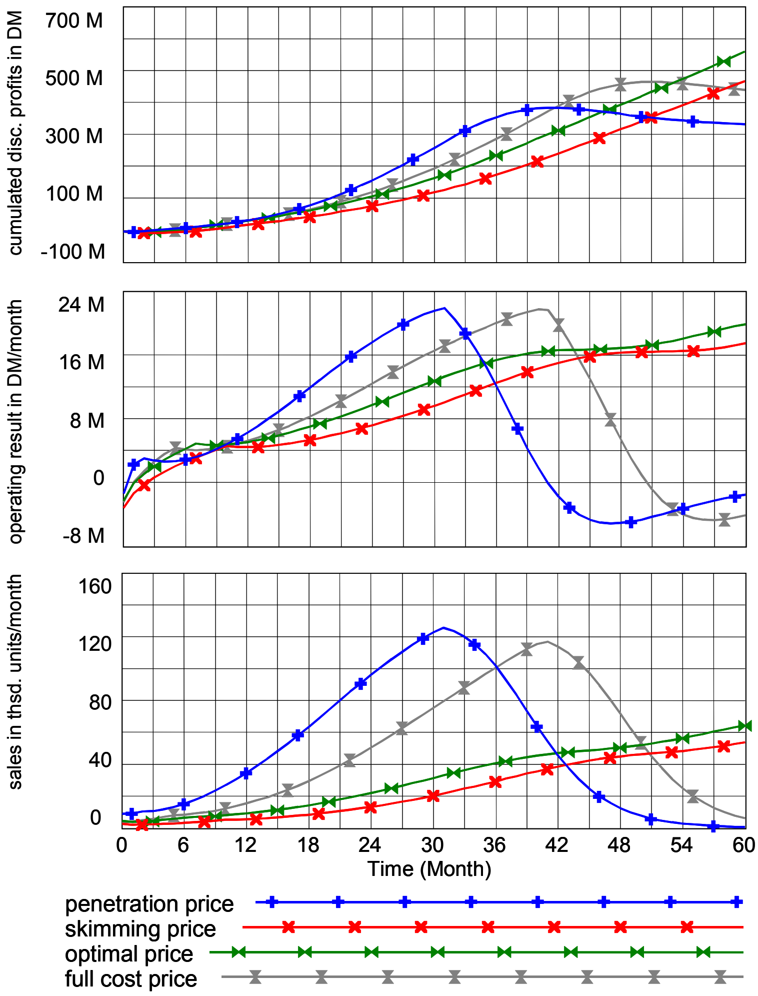


Figure 9: Comparison of the outcome of pricing strategies

Figure 9 also indicates a disadvantage of the penetration strategy. Since the market is completely penetrated already after period 54, there is only little time to develop and introduce a new product in the market successfully. The slower market development of the skimming and optimum price strategy leaves more time for the development of a new product, but the attractive profit situation and the slow development also increase the risk that competitors might enter the market. In a dynamic demand situation where prices influence market growth, where substitution or competition can occur, and where delivery delays eventually accelerate the decision of potential buyers to turn to other products, a strategy of rapid market penetration seems to be the most promising one. It will therefore be the basis for the following simulation runs investigating manufacturing's role in innovations management.

The role of the manufacturing function of a plant is important for the successful management of innovations. Manufacturing has to provide sufficient capacity to produce the goods sold. The investments to adjust capacity influence a company's ability to meet demand and deliver on time. Since the model is designed to study the effects of management strategies on the diffusion of technological innovations, it is assumed that the necessary financial resources for the investments are available. The aggregated capacity provided by the company includes both, machinery equipment and production personnel. Since the manufacturing function also has to ensure the quality of the output through dedicating a portion of its total available capacity to quality control, the capacity resources provided by both can be used to either manufacture the products or to assure the desired level of quality. Capacity allocation to improve quality takes away capacity for production. This additional feedback structure—the shaded area at the left in Figure 6—maps the allocation of resources for quality control to the achieved ability to meet product demand. If manufacturing capacity does not meet demand, a temporary reduction of capacity for quality assurance seems a plausible strategy. Quality control resources than are allocated to manufacturing rather than testing whether quality standards are met. In this scenario it would be expected that total cost remain unchanged and the additional manufacturing capacity gained through the reallocation can be used to provide more products to the customers, increase sales and improve the overall results.

Figure 10 shows the simulation assuming the same scenario as the base mode together with penetration prices and reduced quality resources if demand exceeds production capacity. It also shows a quality index plotted as an additional variable. Quality is defined to be 1, if the actual quality capacity equals a standard value of quality resources necessary. It is assumed that 10% of total production capacity is necessary to assure 100% quality. For values above standard, quality is better; for values below, it is poorer. The simulation indicates that the policy of reduced quality resources successfully decreases the discrepancy between demand and production as seen in the reference mode of Figure 8, leading to a higher ability to deliver. This results from the increased proportion of capacity used for production and an additional effect resulting from lower product quality, which decreases the demand and slows down the product life cycle.

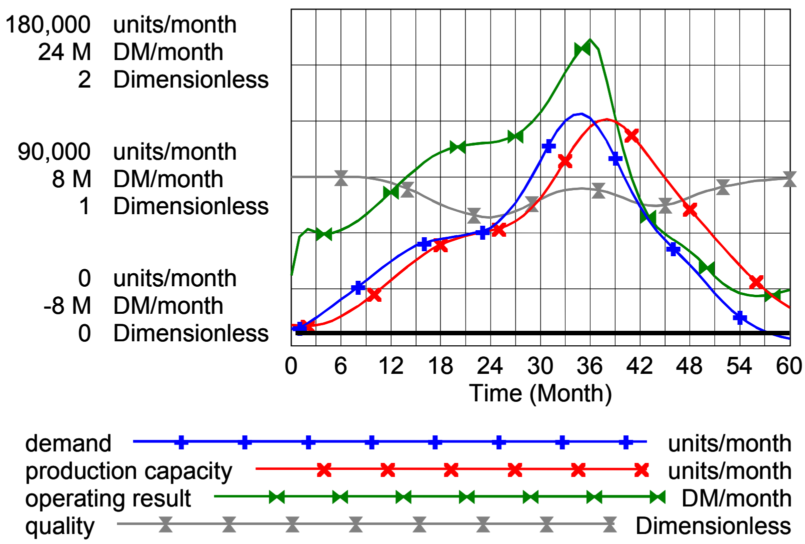


Figure 10: Reduced quality control

Although the maximum sales are nearly the same in the simulation of reduced quality control strategy, the peek demand occurs around 5 months later. Instead of gaining higher sales only the shape of the life cycle changed. However, operating results had improved, in particular the sharp decline of profits in the base mode of the simulation could be slowed down. In the base mode even periods of losses due to the inflexibility in capacity adjustments occurred.

The reduced quality control strategy caused a slower capacity built-up and therefore when product sales declined capacity adjustment was easier to achieve. From the financial point of view the strategies, penetration prices and reduced quality control resources if demand exceeds capacity fit quiet well.

The results are different if a strategy of quality reduction is used in combination with a strategy of skimming or optimum pricing. Figure 11 shows the outcome of cumulated discounted profits for the reduced quality strategy together with penetration prices and skimming prices. Additionally, for comparison the development of the reference mode—i.e. the respective simulations of pricing strategies without quality adjustment—is shown. The behavior indicates that in the case of skimming prices, quality reductions slow down the development of the market and cumulated profits significantly.

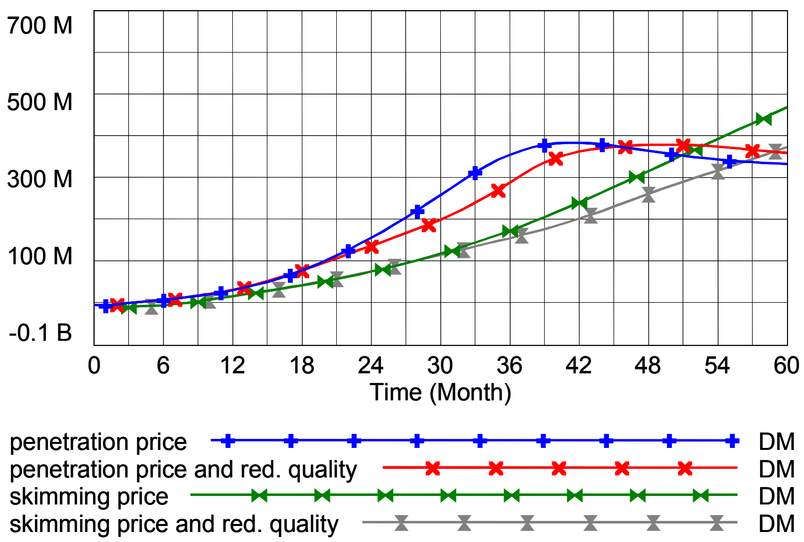


Figure 11: Penetration vs. skimming pricing in combination with quality control strategies

The simulations raise the question whether emphasizing quality if demand is higher than capacity would be a more appropriate way to react. As the upper part of Figure 12 points out, the strategy of emphasized quality leads to an accelerated product life cycle in the case of the penetration pricing strategy. Tremendous capacity built-up is necessary after the introduction of the new product. As demand declines, a plenty of capacity is idle, causing significant losses during the downswing of the product life cycle.

Emphasizing quality turns out to be more effective in the case of skimming or optimum prices. The additional demand gained from quality improvements also accelerates the product life cycle, but at a much slower rate. Emphasizing quality in combination with skimming or optimum prices leads to improved cumulated profits, compared to both, the simulation without quality reaction and the quality reduction run.

The simulations show the importance of a detailed judgment of strategic choices. Strategies must be consistent with each other and with the real world structures mapped by the model. The simulations above assume a situation without existing or potential competition. In such an environment there is no interest paid for fast market penetration. Hence, a penetration pricing strategy is the most unfavorable alternative. However, this changes if structural elements are added to the model, which incorporate competition or substitution.

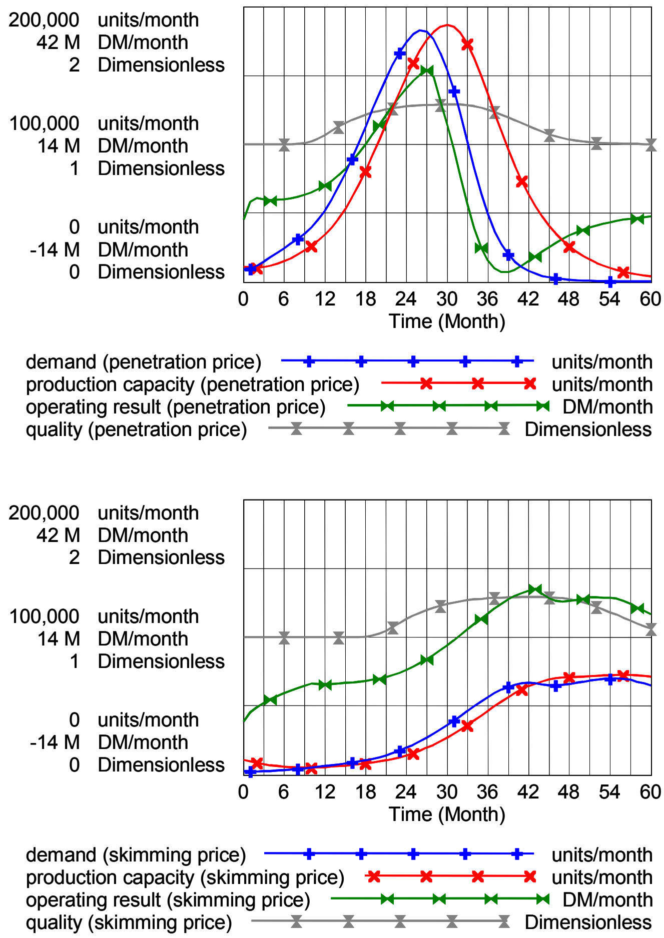


Figure 12: Emphasized quality in all innovation stages

2.2.2. Oligopolistic Models of Innovation Diffusion

The model discussed above is useful to improve the understanding of innovation dynamics as influenced by the interactions of potential customer and adopters and strategic behavior of the company. However, it is limited to companies operating in monopolistic markets, or it can serve as an aggregated model for a whole industry. The model does not reflect the problems that are caused by competition among existing and potential competitors, like e.g. in oligopolistic markets. For this reason, the coarse structure of the model of innovation diffusion has to be extended. Figure 6 already considered the structures to model the loss of demand to a competitor (the shaded area in the middle). Lost demand is represented as a process equivalent to the imitative demand from equation (6). The calculation of lost demand starts in period 15 through an initial switching of a potential customer to the competitor. This switch starts a process that drives demand for the competitors' products and it is influenced through the quality the company offers. If the company offers poor quality, more potential customers and market potential from the untapped market will directly move to the competitor. The accumulation of lost demand corresponds to the number of adopters the competitors gained over time. Simulations with these additional structures offer some additional insights (see Figure 13).

Penetration pricing leads again to the fastest market development. In the competitive surrounding, however, emphasizing quality accelerates the market development and leads to better performance than quality reductions. This is in contrast to the simulations without competition shown in Figure 10 to Figure 12. Skimming prices in combination with reduced quality control shows the poorest financial and market performance. A strategy of reduced quality control causes in the competitive environment the demand to increase at a slower rate than in the base run, where no quality adjustments were made when demand exceeded capacity. Quality reductions lead in both cases, the skimming and the penetration price scenario, to the poorest performance.

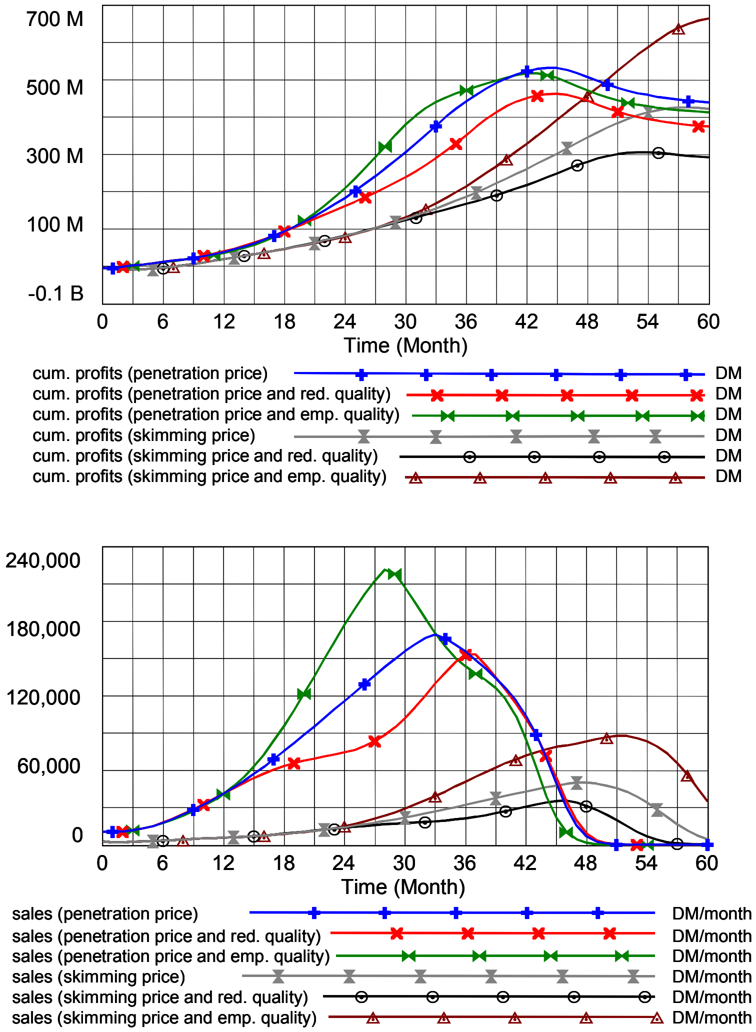


Figure 13: Behavior of the base model including simple competitive structures

In the model discussed so far the internal corporate structures of the competitor are not explicitly represented and the diffusion pattern of lost demand only includes imitative behavior. Since the purpose of the model is to show the effects resulting from competitors entering in an existing market, this level of detail is sufficient. However, to generate diffusion patterns that are influenced by corporate decisions and the resulting interactions of the different competitors in a market, a different and more sophisticated way to incorporate competition is needed.

To model different companies a subscript i (i=1,2,...,k) representing a particular company is introduced as a convenient and efficient way to model the different competitors. In a competitive innovation diffusion model the calculation of innovative and imitative demand of a company has to be modified. Equation (1), which determines the innovative demand in a monopolistic situation, becomes (14)[4]. To ensure that each company will have the same share nopolistic situation, becomes (14)[4]. To ensure that each company will have the same share of innovative demand as long as there is no differentiation among the competitors' products through pricing, advertising quality or market entry time, the coefficient of innovation α has to be divided by the number of competitors. Without changing the absolute value of the coefficient of innovation α, this guarantees that the number of innovative buyers is not higher than in the monopolistic. The subscript i in the coefficient of innovation, also has to consider the decisions of a company regarding product differentiation, e.g., pricing decisions. Since the number of competitors may vary over time, a third modification is necessary. The term φ_i, which represents a factor to model different dates of market entry, is introduced. It takes the value 1 if a company i is present at the market, otherwise it is 0. Hence, the demand of company i is 0, as long as it is not present at the market and $\sum_{i=1}^{k}\varphi_i$ represents the actual number of competitors. The variable potential customers PC has no subscript because all companies in the market compete for a common group of potential customers, whereas innovative demand has to be calculated for each company and are modeled as subscripted variables.

$$\mathrm{D}_i^{Inno} = \frac{\alpha_i}{\mathrm{NC}} \cdot PC \cdot \varphi_\mathrm{i} \tag{14}$$

with:

α_i	coefficient of innovation company i
NC	number of active competitors $=\sum_{i=1}^{k}\varphi_i$
φ_i	factor of market presence company i
i	subscript representing the companies $i=(1,2,\ldots,k)$

The buying decisions of imitators are influenced by observation of, or communication with the adopters (ADOP). In a competitive environment two alternative approaches can be used to calculate imitative demand. These different approaches are a result of different interpretations of the object of the communication processes (Milling and Maier 1996, Maier 1995b). In the first interpretation, the 'product related communication', the adopters of a particular company's product communicate information about the product they have purchased e.g., an electronic device like a DVD-player of a particular company. In this case, the calculation of imitative demand has to consider the number of potential contacts between the potential customers PC—which is the same for all competitors—and the adopters of the products of company i ($\mathrm{ADOP_i}$) as shown in (15).

$$\mathrm{D_i^{Imit}} = \frac{\beta_i}{\mathrm{N}} \cdot \mathrm{A}DOP_\mathrm{i} \cdot \mathrm{P}C \cdot \varphi_\mathrm{i} \tag{15}$$

with:

β_i	coefficient of imitation company i
N	initial value of market potential

The second interpretation about the object of communication is the 'product form related communication'. Here, the adopters communicate information about a product form, for example, DVD-players in general and not about a DVD-player of a particular company. The equation to calculate imitative demand for the model of product form related communication is shown in (16). The sum of adopters of each company i ($\sum_{i=1}^{k} \mathrm{ADOP_i}$) represents the total number of adopters in the market, i.e., the cumulated product purchases of all companies i. The product of the total adopters and the potential customers then represents the total number of potential contacts in the market. Imitative demand of a company i depends on the share of total adopters $\frac{\mathrm{A}DOP_{\mathrm{i}}}{\sum_{i=1}^{k} \mathrm{ADOP_i}}$ this company holds.

$$\mathrm{D_i^{Imit}} = \frac{\beta_{\mathrm{i}}}{\mathrm{N}} \cdot \frac{\mathrm{A}DOP_{\mathrm{i}}}{\sum_{i=1}^{k} \mathrm{ADOP_i}} \cdot \mathrm{P}C \cdot \sum_{i=1}^{k} \mathrm{ADOP_i} \cdot \varphi_i \tag{16}$$

Equation (16) can be transformed into equation (15), through reducing the number of adopters of the product form of $\sum_{i=1}^{k} \mathrm{ADOP_i}$. If the term that represents a company's share of the total adopters of a market $\frac{\mathrm{A}DOP_{\mathrm{i}}}{\sum_{i=1}^{k} \mathrm{ADOP_i}}$ is raised to the power of γ as in (17), weaker ($0 < \gamma < 1$) or stronger ($\gamma > 1$) influences of a company's share of total adopters on demand can be represented explicitly (Milling and Maier 1996)[5]. For $\gamma = 1$, equation (17) is identical to equation (16).

$$\mathrm{D_i^{Imit}} = \frac{\beta_{\mathrm{i}}}{\mathrm{N}} \cdot \left(\frac{\mathrm{A}DOP_{\mathrm{i}}}{\sum_{i=1}^{k} \mathrm{ADOP_i}} \right)^{\gamma} \cdot \mathrm{P}C \cdot \sum_{i=1}^{k} \mathrm{ADOP_i} \cdot \varphi_i \tag{17}$$

Figure 14 shows the effects of a company's share of the total adopters for different γ. For a given share of total adopters this means: the higher γ, the lower is the value of the term $\left(\frac{\mathrm{A}DOP_{\mathrm{i}}}{\sum_{i=1}^{k} \mathrm{ADOP_i}} \right)^{\gamma}$ and the stronger is the importance of a high share of total adopters. The parameter γ can be interpreted as a measure of the importance of customer loyalty.

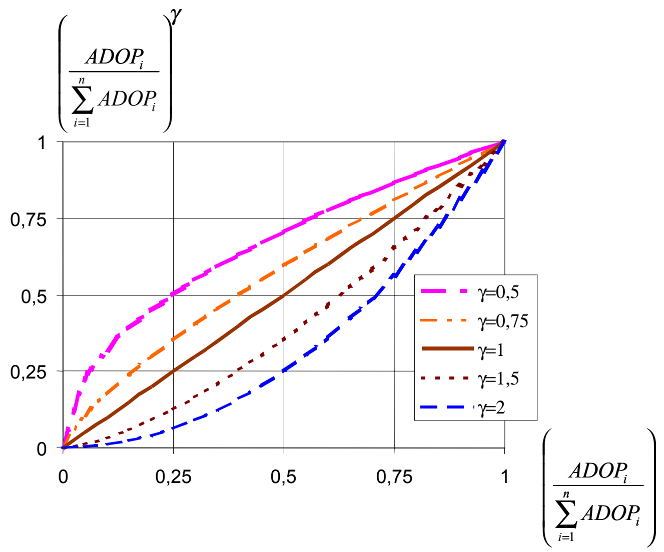


Figure 14: Effects of a company's share of adopters for different γ

Figure 15 illustrates the coarse structure of an oligopolistic innovation diffusion model as described in equation (14) and (17). The hexahedron at the top represents the stock of potential customers PC for the whole market. The blocks with the different shading represent for each company i the level of adopters, i.e., the cumulated sales of the company. The total number of adopters of the product form corresponds to the addition of these blocks.

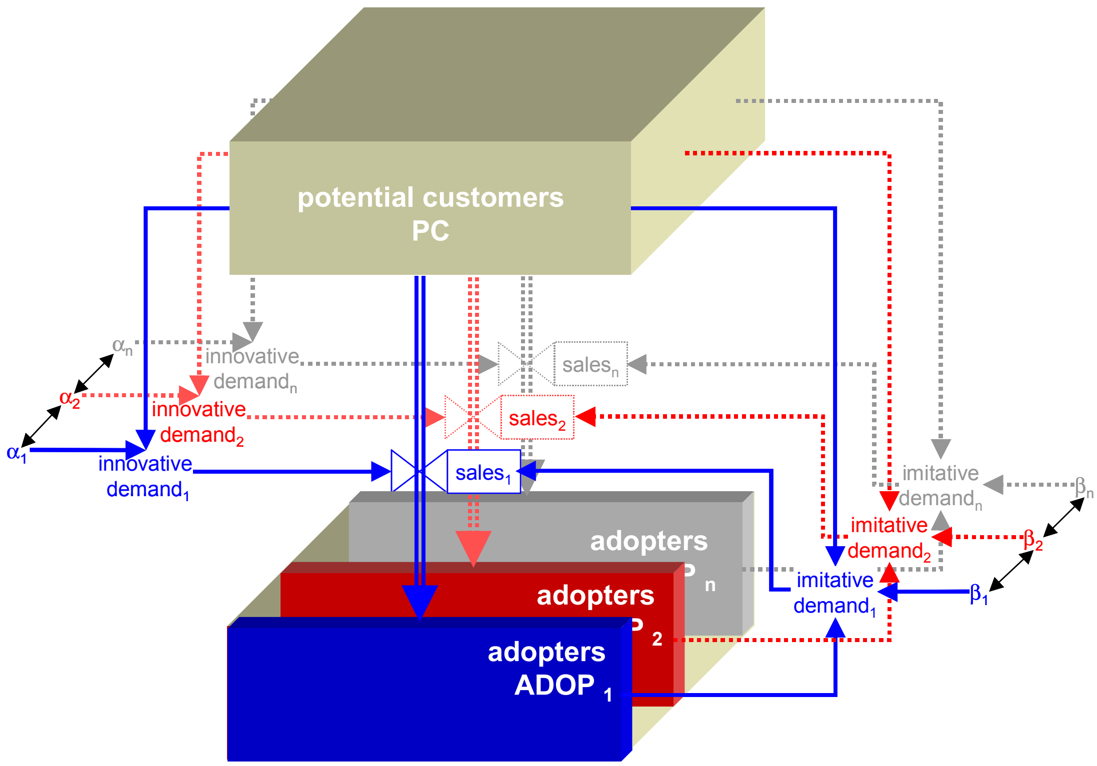


Figure 15: Coarse structure of an oligopolistic innovation diffusion model

Since the sales are calculated separately for each company i there are n outflows from the stock of potential customers to the adopters. Again, sales comprise innovative and imitative demand, which are influenced by the coefficient of innovation α_i and imitation β_i. Both coefficients are influenced by managerial decisions of each company i like pricing, advertising, quality, market entry timing, etc. and measure the relative influence of the decisions compared to the competitor's decisions. Therefore the value α_i and β_i not only depends on the decisions of company i, it also depends on the competitor's decisions. Both variables are crucial for the speed and the maximum volume of demand for the products of a company i.

Figure 16 shows the results of a model simulation based on equation (14) for innovative demand and (17) for imitative demand with the effects of a market entry delay of the second company (see Maier 1995b, and Milling and Maier 1996 and Maier 1998 for a detailed description). Several model simulations have been made assuming a market entry delay of company 2 between 0 and 12 months. The factor γ is set to 0.75; the influence of other decision variables is switched off.

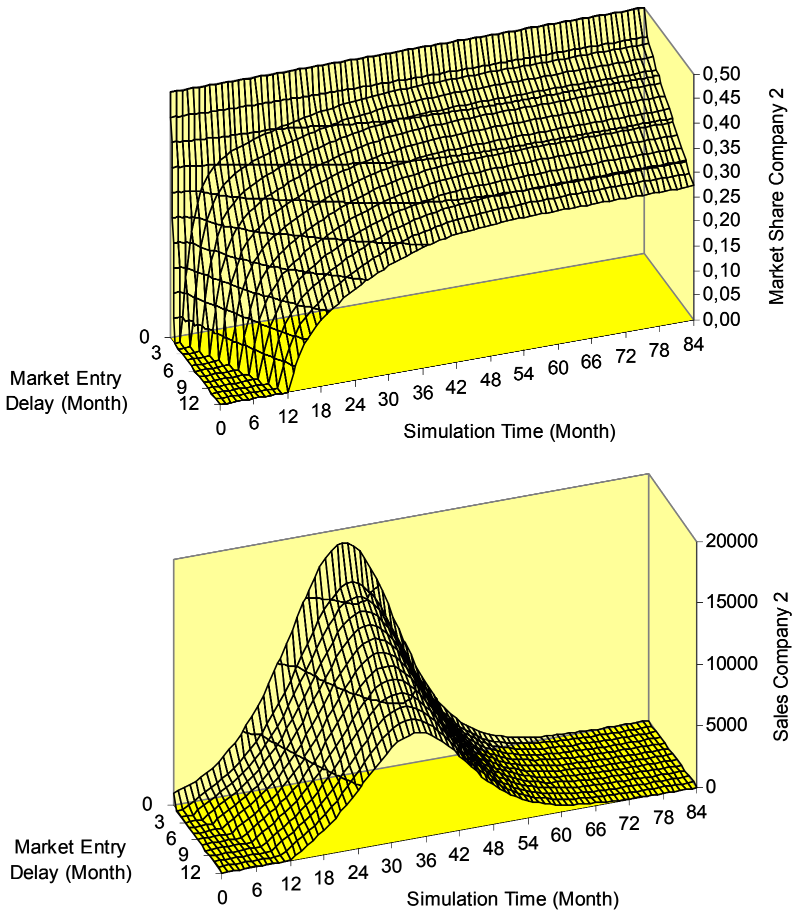


Figure 16: Follower's market share and sales for different market entry times

The plots in Figure 16 show the development of market share and sales of the second company over time. Since there is no further product differentiation, both competitors have the same market share when they enter it at the same time. With each month delay of the second company the market share that can be achieved at the end of the simulation decreases. A three months delay reduces the finally achieved market share to 40%; a 12-month delay even causes a decrease in market share down to approximately 25%. Accordingly, the maximum sales volume decreases significantly with each month delay in market entry time.

2.2.3. Substitution Models of Innovation Diffusion

Academic research only rarely touches the transition of one innovation to succeeding, even more advanced and more attractive products (exceptions are e.g., Linstone and Sahal 1976, Norton and Bass 1987, Fisher and Pry 1971, Norton and Bass 1992, Milling 1991b, Maier 1998). As Figure 17 shows for the example of DRAM chips, in innovative markets the substitution between technologies occurs rather rapidly. Very short life cycles and a dramatic decay in prices, starting immediately after introduction, characterize this market. Although, each new generation brought a quadrupling of sales, the short life cycles and the decay of prices leaves only little time for a company to earn an adequate return on its investment (Abernathy and Utterback 1988, Steele 1989, Bye and Chanaron 1995). Most models discussed in literature concentrate on—and thereby isolate—the short-term dynamics of an innovation. These models do not reflect the substitution processes between products that take place as technologies advance. However, to improve the effectiveness of managerial decision-making, substitution processes have to be considered and represented endogenously. Most of the System Dynamics work in this area either focuses on macroeconomic perspectives (Graham and Senge 1980, Forrester 1981), on a specific branch of industry (Homer 1983, 1987), or on particular behavior aspects (Paich and Sterman 1993).

The behavior modes shown in Figure 17 highlight the importance of adequate capacity built-up to assure on-time delivery if demand gains momentum, because in such a dynamic environment delivery delays can cause a permanent loss of customers. The fast declining prices shorten the period where high prices can be used to compensate research and development expenditures. An adequate response to this behavior might be a strategy of high pricing together with an early investment in sufficient production capacity. However, such a strategy implies high fixed cost and little flexibility if demand is overestimated. High prices in the early stages of the life cycle may cause slow market penetration reducing the benefits of large production volumes. Thus, in a System Dynamics model dealing with innovation dynamics the aspects of substitution should be considered because of the complexity of the system, the risks involved, the need for improved understanding of the dynamics, and the necessity of rational decision making.

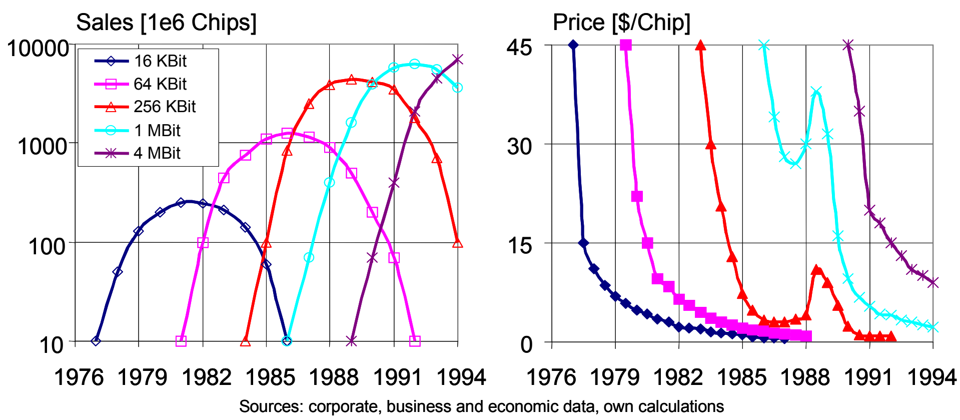


Figure 17: Sales volume and price development of DRAM chips

Substitution is not limited to a competitive environment. Even in a monopolistic environment companies have to deal with the problems of substituting older products with technically more advanced new products. Substitution can be seen as a special sort of competition: competition between subsequent product generations. To a large part, the problems of successfully managing R&D, innovation and diffusion result from competition through the introduction of subsequent and substituting product generations either by the own company or by other firms in the market. Substitutional products compete for the same group of potential customers. On the one side, introducing a new product too early cannibalizes the older products of a company, and on the other side, waiting too long could result in a sharp decline of sales caused by competitors entering the market with more advanced products. Only a few models deal with these problems of substitution. Most authors seek for simple mathematical representations of substitution processes allowing parameter estimation on the basis of empirical data (e.g., Norton/Bass 1987, Fisher/Pry 1971, Norton/Bass 1992). Their aim is not the explanation of the underlying structures and the forces driving the substitution processes. A system dynamics model allows explaining these dynamics of substitutional processes and helps to search levers to control the processes. Such a model will be described in the following. The model structure considers the substitution processes of the successive products of a single company, for the reason of simplicity (see also Maier 1998). It describes the structures of a quasi-monopolistic company dealing with the innovation and diffusion processes of successive product generations.

Thinking about the structure of a substitution model, the question arises whether the competitive model of innovation diffusion shown in equation (14) and (17) and in Figure 15 is capable to reproduce the diffusion and substitution processes which can be observed in the market of microprocessors. Therefore the subscript i from the competitive model could be reinterpreted as different product generations (not different companies) and the term φ_i would represent the market presence of the different product generations.

Taking the sales of microprocessor generations as a reference mode, the simulation in Figure 18 with different market entry times for successive products indicates, that the competitive structure is insufficient for several reasons. First, in the market of computer hardware or software one can observe a strong increase in demand for subsequent product generations. In contrast to this, the model simulation generates product life cycles with decreasing maximum sales volumes for each successive product generation.

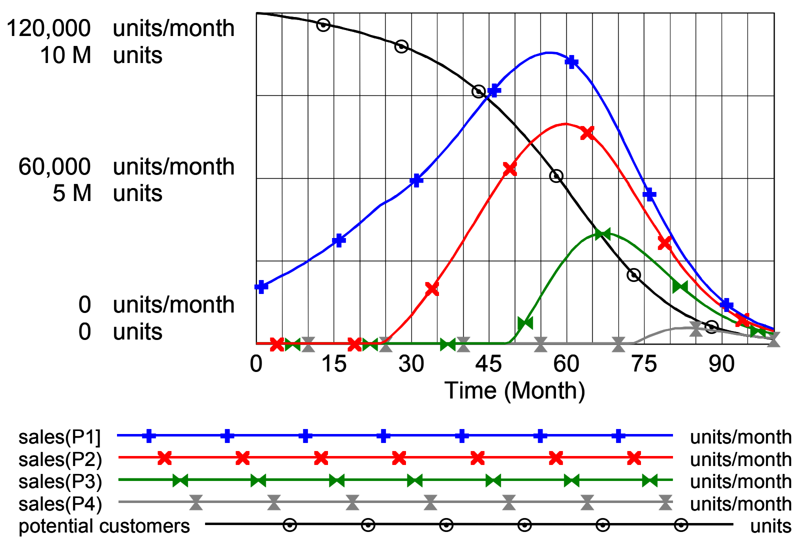


Figure 18: Behavior of the reinterpreted competitive model

The main cause for this behavior is the continuously decreasing number of potential customers. Customers who have already bought an earlier product generation cannot buy a product of a successive generation. In Figure 15 there is only an outflow from the potential customers to the stock of adopters. Since, e.g. repeat purchases caused by the obsolescence of a product are not considered, there is no flow back from the adopters to the potential customers. As a second reason the market potential is not increased through inflows from an untapped market and the number of potential customer decreases over time with each product sold. Corresponding structural elements have to be included to model substitution processes adequately.

The structure of the diffusion module of the substitution model is shown in Figure 19. The market module consists of the level variables Potential Customer *(PC)*, Untapped Market *(UM)* and k level variables for the adopters *(ADOP)*, where k represents the number of different product generations to be modeled (see Maier 1998 for the model equations). The first level variable (Potential Customers) represents the remaining market potential of each period for all product generations, a contrast to the Norton/Bass model which requires a separate market potential for each product generation (Norton/Bass 1987). Norton and Bass (unrealistically) divide the homogeneous group of potential customers into different market potentials.

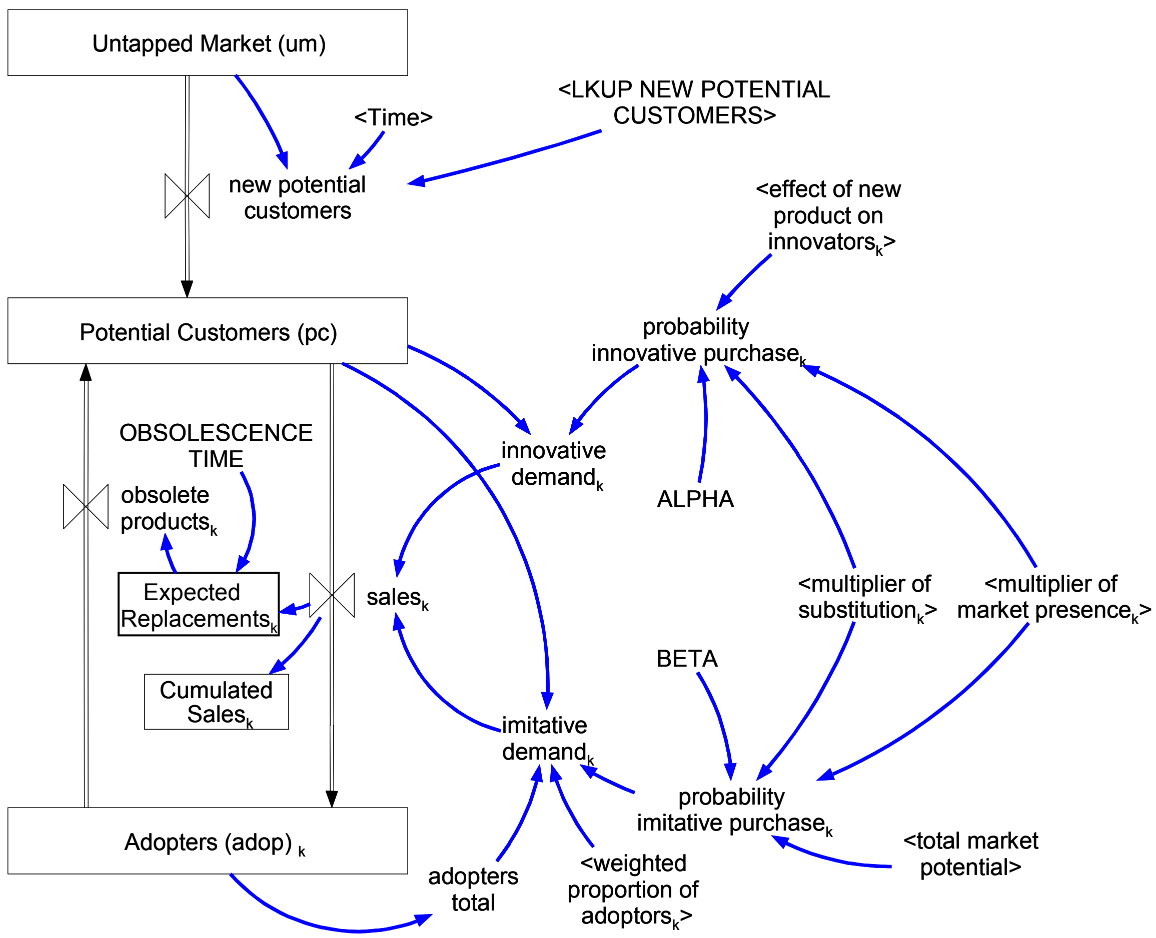


Figure 19: Coarse structure of the substitution model

Here, potential customers are treated as one group, which is reduced by the sales of all different product generations k of a company in a period of time (sales$_k$) and increased by the inflow of New Potential Customers coming from the untapped market. An additional inflow stems from former customers of the different product generations who are willing to purchase a product repeatedly due to product obsolescence (obsolete products$_k$). The level Untapped Market represents the number of persons that can become potential customers. If the technical capabilities of the products fit the needs of the persons of the untapped market, or if the prices of the product are reduced and they become affordable, new potential customers flow from the untapped market to the stock of potential customers.

Adopters are a subscripted variable, where the subscript k represents the different product generations. The level of the Adopters of each product generation k is increased by the sales of the product. Product obsolescence causes the number of adopters to decrease and increases the number of potential customers. According to the competitive model described in equation 14 and 17, the sales of each product generation k consist of innovative demand and imitative demand. The coefficients of innovation and imitation α_k and β_k then represent the probability of innovative or imitative purchases. These coefficients are modified by the multiplier of market presence φ_k and the multiplier of substitution that comprises the mechanisms to control the substitution and diffusion process. It is influenced by the technical capability of a product generation and the price of a product compared to the preceding generations. It increases with improvements of the technical capability and falling prices. Under the precondition that the remaining market potential is still high enough, this multiplier drives the success of the new product. Since innovators by definition are likely to buy the newest product generation, a multiplier representing the effects of new products on innovators modifies the probability of innovative purchases. It decreases the probability of an innovative purchase of a product generation k-1, if a new product generation k is introduced to the market.

This model is able to generate the typical product life cycles for different subsequent and substitutive products. The behavioral validity of the substitution model was tested against historical data for different generations of Intel microprocessors (80286, 80386, 80486, and Pentium). The comparative plot of cumulative sales computed with the model and cumulative sales observed in reality shown in Figure 20 gives an impression of the good fit. [6] The R^2 for the data series of the 4 product generation is between 0.959 and 0.998.

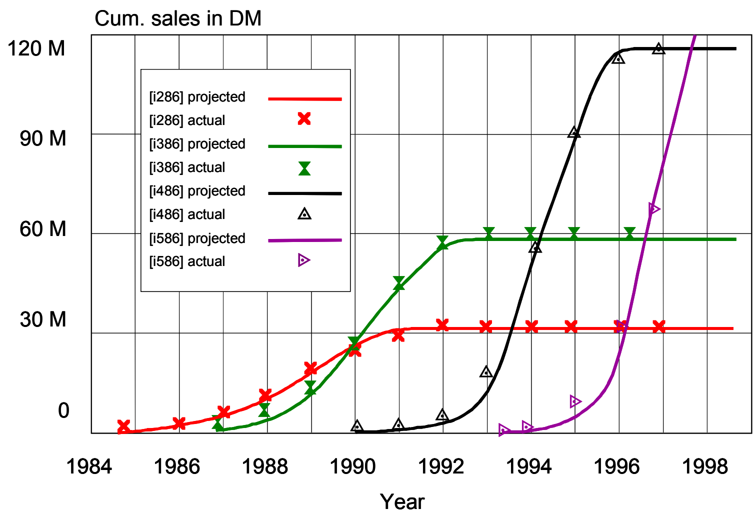


Figure 20: Model behavior and empirical data

Although the curve fit is very good, the model is sensitive to parameter changes. Time to market, technical capability, price, and the flow of new potential customers are treated as exogenous variables. Their values over time are taken from historical data wherever available or are estimates based on various sources[7]. Although the model reacts to these exogenous inputs, assuming e.g., a price path or market entry time other than the empirical data, still leads to robust and plausible model behavior. It can be stated that the model has proven its usefulness as a simulator for policy making in the case of substitution among successive innovations limited to the case of a monopolistic market or an industry.

The development of this model provided useful insights in the dynamics of substitution. It showed that for the simulation of subsequent products like microprocessors traditional models of innovation diffusion are insufficient. Generating product life cycles that fit historical data was not possible without structural changes—adding repeat purchases and the flow from the untapped market to a traditional diffusion model. The goodness of fit was first of all reached through a more adequate model structure and only in a second step through improved parameter calibration. This confirms Forrester's paradigm of structure influences behavior (Forrester 1968).

3. Integrating R&D with Innovation Diffusion Models

The diffusion models discussed above generate the spread of a new product in the market place under monopolistic and oligopolistic conditions as well as the behavior of evolving product generations. These models do not consider the stages of new product development. However, new products have to be developed and tested before they can be introduced into the market. A costly, lengthy and risky period of R&D has to be passed successfully. The market cycles of new products become shorter and therefore reduce the time available to earn a sufficient return on investment, while the development stage tends to become longer and more costly. These diverging trends show the importance of a holistic view of both, the development stage of new products at the one side and the stages of innovation and diffusion on the other. Therefore, a comprehensive investigation of innovation processes must cover both, the development and the market cycle of new products. In the remainder, a comprehensive model comprising the evolutionary process of R&D—discussed in chapter 2.1—and an oligopolistic innovation diffusion with subsequent product generations serves to investigate the interrelations between the stages of innovation processes. The integration of both modules is shown in Figure 21.

The volume and the intensity of the research and development activities of a company feed the R&D-process. The number of research personnel determines the volume. Since R&D personnel requires resources like laboratory equipment, material for experiments etc., the intensity of R&D depends on the budget available for each person working in the R&D sector. This information is calculated in the sector of R&D planning of a comprehensive corporate model which also includes policies about resource allocation within the research and development stages, i.e. mainly the question of how much to spend on which new product development project.

Depending on the volume and the intensity of R&D, the technological knowledge of each product generation for each company evolves over time. The module of the R&D process feeds back the current state of the technological knowledge for each company and product generation. The module of the companies and the market is a Vensim-based System Dynamics model. It comprises the core model of product life cycles in an oligopolistic environment as described in 2.2.1, and sectors modeling production, pricing strategies, market entry timing, or quality.

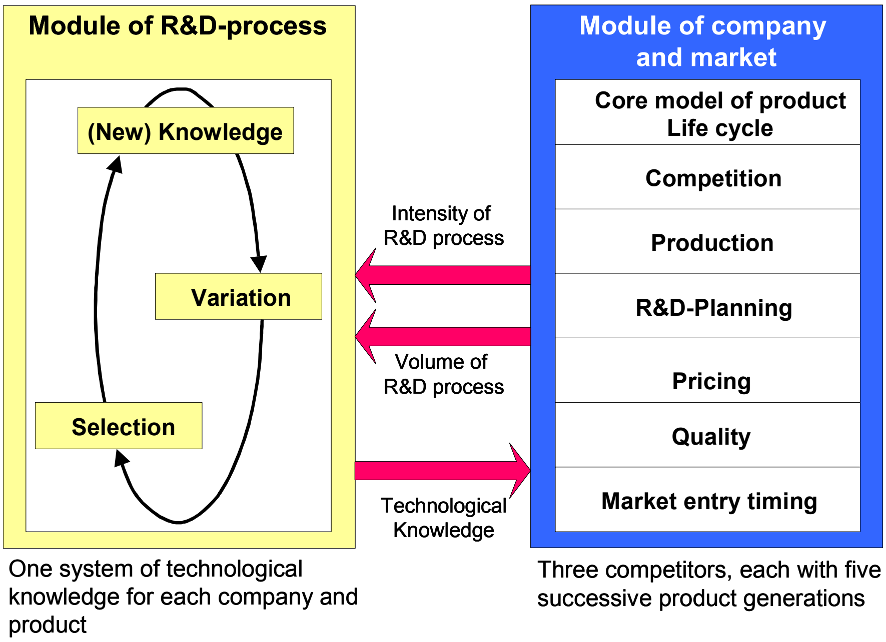


Figure 21: Linking R&D-processes with corporate and market dynamics

3.1. Basic Behavior of the Model

The Vensim-based System Dynamics model linked to the C-written evolutionary algorithm which models the R&D process as described is the basis for the analysis of the inter-stage feedback relations. First the basic assumptions and behavior of the model will be described briefly. The model comprises the structures for two competitors each of which can introduce five successive product generations. The initial values of the model ensure that all competitors start from the same point. All firms have already introduced the first product generation and share the market equally. The resources generated are used to develop the second product generation. In the base run each company follows the same set of strategies. Therefore, except for minor differences resulting from the stochastic nature of the evolutionary algorithm, they show the same behavior over time. Figure 22 provides a simulation run of the model with all modules and sectors coupled.

The curves show for a single company the development of the sales of the products and the total sales. They emphasize the importance of a steady flow of new and improved products. Without on-time replacement of older products, the total sales of the products will flatten or deteriorate like in the simulation around periods 36, 96, and 116. When the evolution algorithm is run as a stand-alone module—without interference from the market and company module—it generates the succession of products with increasing levels of sophistication (Figure 4). If both modules are linked together the model creates S-shaped curves enveloping the technological development of individual innovations for each company shown in Figure 22. Each product generation has a higher technological potential, i.e. in terms of the evolutionary algorithm, the number of rows in the matrices is increasing over the product generations. The knowledge developed for the preceding product generations partly can be used by the successive product generations. For this reason product generation 3, 4 and 5 start at a level different from zero.

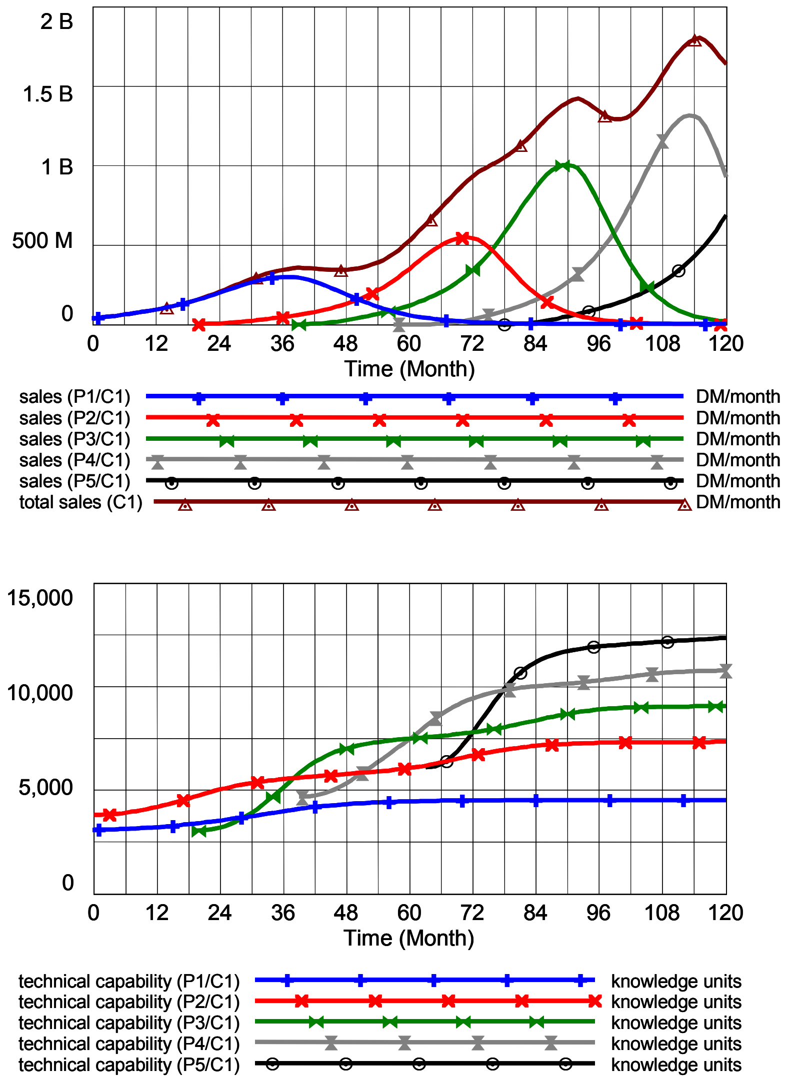


Figure 22: Exemplary behavior of the integrated innovation model

3.2. Interactions between the Stages of Invention, Innovation and Diffusion

The comprehensive model serves as a tool to investigate the interactions between the different stages of the holistic innovation process. In a dynamic environment like e.g. the computer industry, where investments in R&D and manufacturing equipment are high, the product life cycles are short, and time-to-market as well as time-to-volume are essential variables (Bower and Hout 1988), it is important to understand the dynamic consequences of decisions and strategies in the different areas. As several studies report, a six months delay of the market introduction of a new product can reduce overall earnings up to 33% (Dumaine 1989). Substantial production cost or R&D budget overruns have far less impact. Similar results are confirmed by our own analyses (Milling and Maier 1996). Figure 23 describes some of the important feedback loops linking the process of invention to the processes and drivers of the stage of innovation and diffusion.

Central element in the figure is the calculation of the sales of a company according to equations (14) and (17). The coefficients of innovation and imitation are influenced by the multiplier of relative competitive advantage or disadvantage, which depends on the relative technical capability and the price advantage of company compared to its competitors. The technical capability of the products is influenced by the strength of its R&D processes. The total amount of R&D expenditures of industrial corporations depends on various factors. Empirical studies have shown that in 1986 almost 60% of the investigated German companies use history-oriented values, like sales volume, profits or R&D budgets of earlier periods, for budgeting (Brockhoff 1987, Kern and Schröder 1977). However, a strategy based on past sales volume activates the positive feedback loop “competing technical capability” (Figure 23). With an increasing number of products sold and growing value of sales the budget and the number of personnel for R&D grow. If the technical capability of a product rises this leads to a competitive advantage. The higher the sales volume, the better is the resulting competitive position. This produces increasing coefficients of innovation and imitation and leads to higher sales. This budgeting strategy implemented and described here causes positive feedback. It is implemented in the model for the next simulation runs (Milling and Maier 1993a, 1993b, Maier 1992).

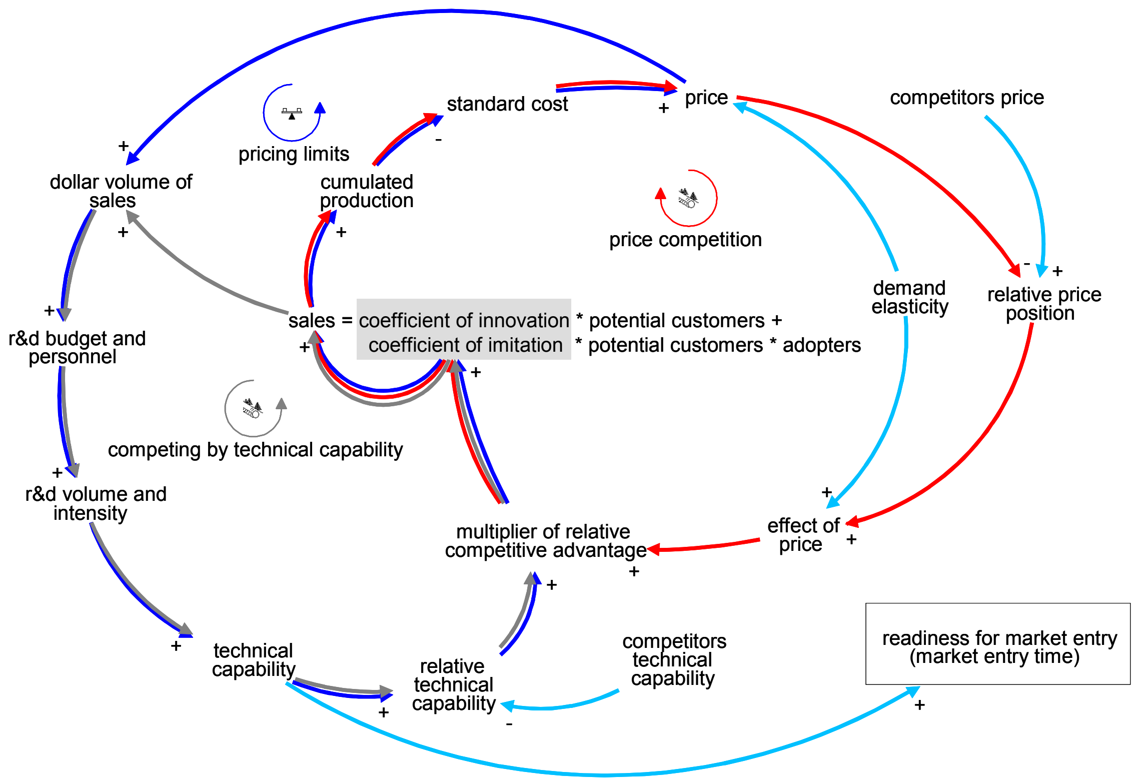


Figure 23: Feedback structure influencing the diffusion process

The second loop “price competition” links pricing strategies to sales volume. The actual price of a product is influenced by three factors. The first factor, standard costs, is endogenous. As cumulated production increases, the experience gained from manufacturing the products leads to a decline in standard cost. The second and third elements influencing the calculation of prices are exogenous elements: parameters that define the pricing strategy and demand elasticity. Through parameter settings different pricing strategies can be activated, each calculating the price of a product based on standard cost. Caused by increasing cumulated production, standard cost fall over the life cycle and prices are also declining. Lower prices affect the relative price and improve the effect of price on the coefficients of innovation and imitation. Higher coefficients again cause increased sales and lead to still more cumulated production.

The loop “pricing limits” reduces the effects of the reinforcing loops described above to some extend. Demand elasticity determines, as described in equations (10) and (11), the profit margin and therefore the base price for the alternative pricing policies. The standard cost and price reductions induce—ceteris paribus—a decrease in the dollar volume of sales and set off all the consequences on the R&D process, the technical know-how, the market entry time and sales shown in the first feedback loop—but in the opposite direction. This and the fact that standard cost can not be reduced endlessly is the reason that this feedback loop will show a goal seeking behavior.

With equivalent initial situations and the same set of strategies, both companies behave in an identical way for all product generations, except some minor stochastic differences caused by the evolution algorithm. If one company has a competitive advantage, the reinforcing feedback loops suggest that this company will achieve a dominating position. In the simulation shown in Figure 24, both competitors have the same competitive position for the first product generation. But the first company will be able to enter the market 2 months earlier than the competitor.

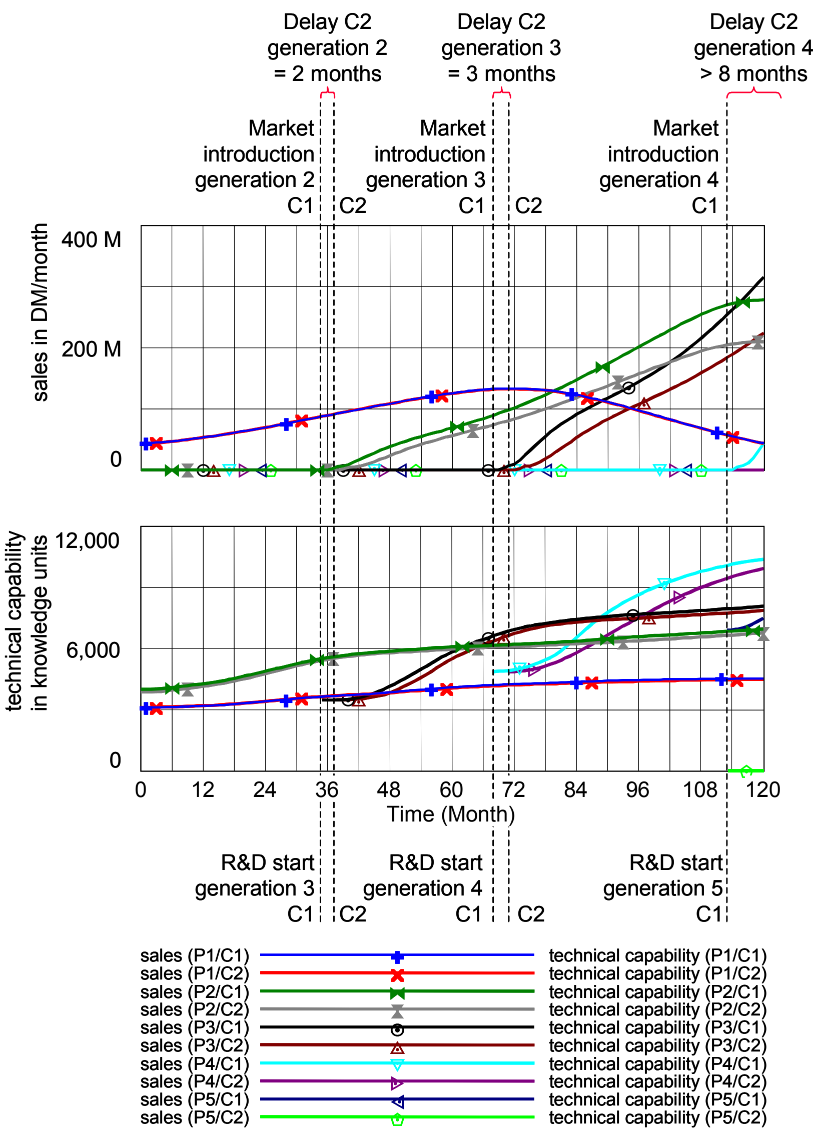


Figure 24: Reinforcing effects of initial competitive advantage

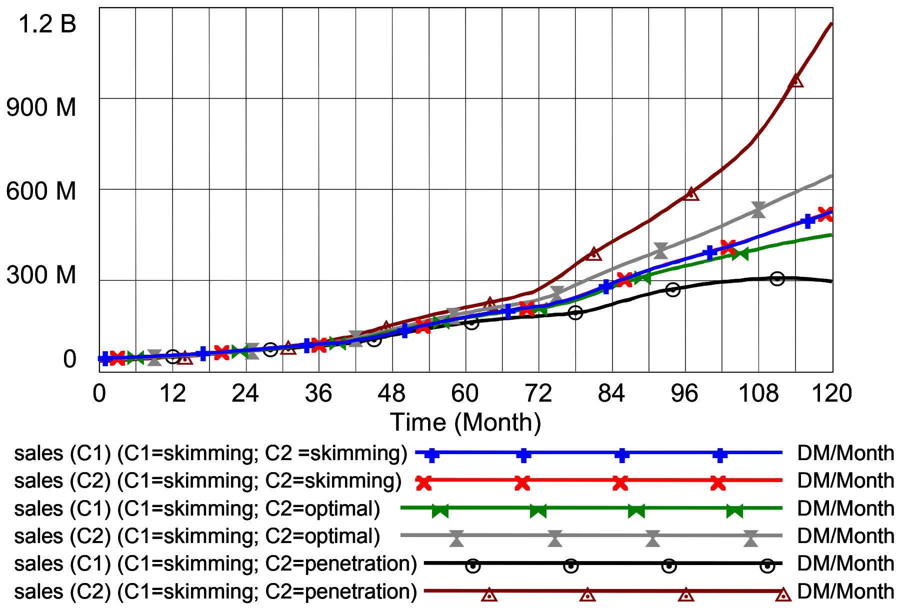
The initial number of elements in the knowledge matrix of the second product generation which owe the value “1” was increased for the second company’s second product generation by a small amount. Both competitors follow a strategy of skimming prices and demand elasticity ε has the value –2. The initial gain in the outcome of the R&D process initiates a process of sustained and continuing competitive advantage for the first company. It will improve continuously, since the positive feedback loop “competing by technical capability” dominates (Milling/Maier 1993a, 1993b, Maier 1992). The first company’s advantage in the market introduction leads to an increasing readiness for market entry. It is able to launch the third product generation 3 months earlier than the follower (company 2). The pioneering company 1 will introduce the fourth product generation in period 112. The follower is not able to introduce its fourth generation before the simulation is stopped i.e. the pioneers advantage has extended to more than 8 months. The first company gained an increased competitive advantage only through the higher initialization of the knowledge system and the dominance of the positive feedback loops. In consequence, the shortened time to market causes higher sales volume over all successive product life cycles. Additionally, the technical capability of both competitors’ product generations shows the same reinforcing effect. The difference between the technical capability of both competitors increases in favor of company 1 until they approach the boundaries of the technology.

3.3. Pricing strategies in the holistic innovation model

Pricing new products is an important aspect of innovation management. Literature discusses a variety of models to find optimal prices (see, e.g., Bass 1980, Robins/Lakhani 1975, Jeuland/Dolan 1982). Usually these models only consider the market stage of a new product and neglect the interactions with the development stage of a new product. Pricing decisions drive not only the diffusion of an innovation; they also have a strong impact on the resources available for research and development. Since the comprehensive innovation model links the stages of developing and introducing a new product, the following simulations will show the impact of pricing strategies in a competitive environment on performance.

In the analysis the first company uses the strategy of skimming price for all product generations. The second company alternatively uses a skimming price strategy in the first model run, myopic profit maximization strategy in the second run, and the strategy of penetration prices in the third run. As in the simulations before, demand elasticity ε is assumed to be –2. The initial conditions are identical, except the price strategy settings. Several criteria are used to judge the advantages or disadvantages of the alternative pricing strategies: sales volume and market position of each competitor for the market performance, cumulated discounted profits as a measure for financial performance and the market entry time to analyze the pricing strategies in the context of time-to-market.

The logic behind the skimming price strategy is to sell new products with high profit margins in the beginning of a life cycle to receive high returns on investment, achieve short pay off periods and high resources for the R&D-process. However, in a dynamic competitive setting the strategy of myopic profit maximization and penetration prices achieve better results (Figure 25). Company 1 which uses a skimming price strategy achieves the lowest sales volume. Myopic profit maximization prices and penetration prices of the second competitor, causes the sales to increase stronger through the combined price and diffusion effect. If both competitors use a skimming price strategy, sales volume develops identical.



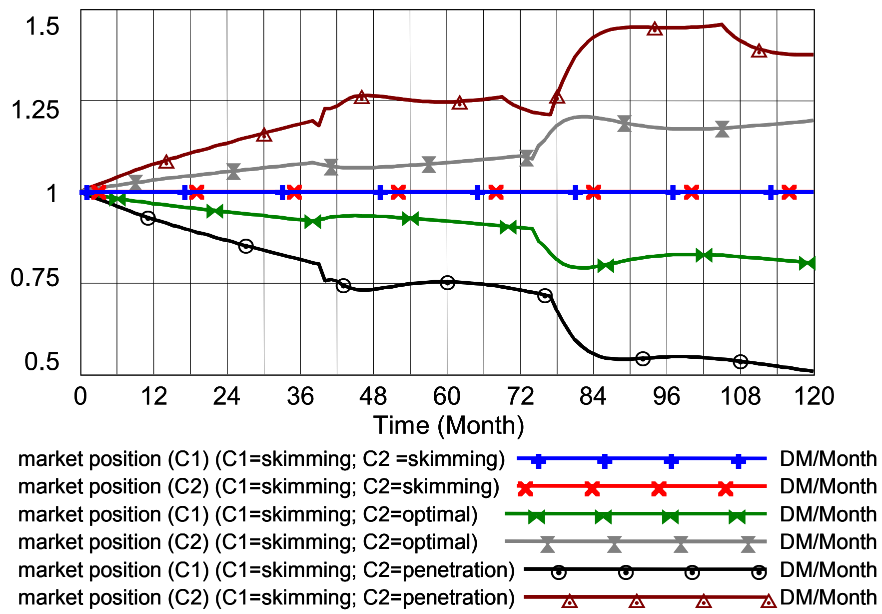


Figure 25: Sales volume and market position for the different pricing strategies

The results are confirmed if the market position is taken into account. The variable market position gives an aggregation of the market share a company has for its different products. For values greater than 1 the market-position is better than that of the competitor. Using the penetration strategy company 2 can improve its market share, achieve higher sales volume and therefore has more resources available for R&D. This enables it to launch new products earlier than company 1. The advantage of time to market is increasing from product generation to product generation as shown in Table 1.

The improvement in time to market for the first company's second product generation is surprising at a first glance. It results from the slightly higher sales volume compared to the use of skimming pricing strategies for both competitors. With the penetration price strategy the second company not only can improve its market position, it also improves its time to market, one of the essential variables in a global competitive setting. Taking cumulative profits into account (Figure 26) one would expect that skimming prices should generate the highest level of cumulated discounted profits. However, with a demand elasticity ε of –2 penetration prices generate the highest results followed by the skimming prices strategy. The myopic profit maximization strategy shows to be the least favorable in terms of cumulated profits.

	Product generation 2			Product generation 3			Product generation 4		
Pricing strategy C2*	C1	C2	Delay C1 to C2	C1	C2	Delay C1 to C2	C1	C2	Delay C1 to C2
skimming prices	38	38	0	71	71	0	n.i.	n.i.	—
profit maximization	36	35	1	71	69	2	n.i.	118	>2
penetration prices	37	35	2	74	66	8	n.i.	102	>8

*C1 uses skimming prices in all simulations;
**n.i. = product was not introduced

Table 1: Consequences of pricing strategies on market entry time

The simulations assumed a price response function with a constant price elasticity ε of –2. Since price elasticity influences both, the demand for a product as well as the price level due to the myopic price setting (cf. Figure 23), the influence of price elasticities have to be investigated before recommendations can be made. Assuming that company 1 uses a strategy of skimming prices and the second competitor follows a strategy of penetration pricing, Figure 27 shows the time path of cumulated discounted profits and market position for ε between –3.2 and –1.2.

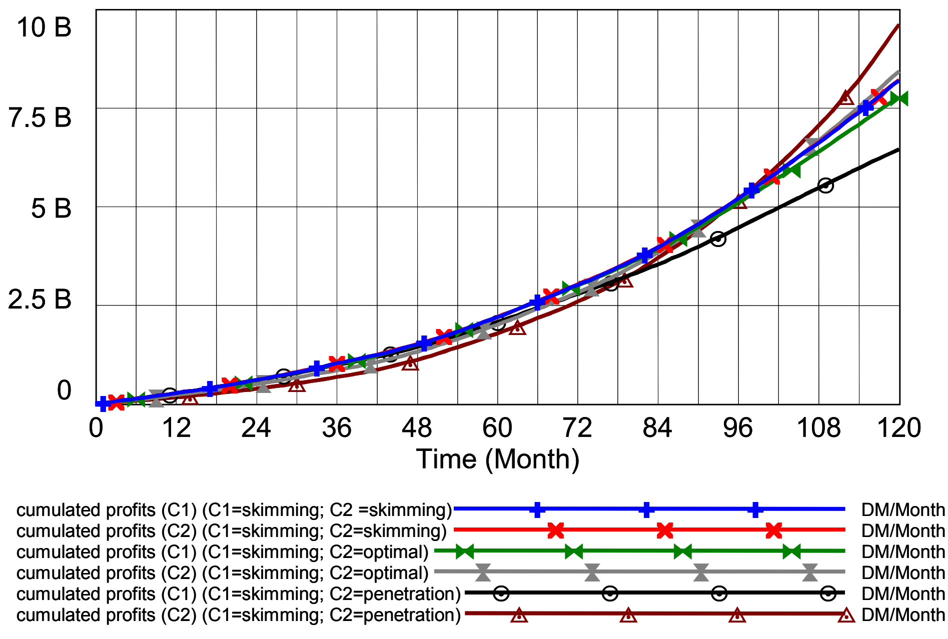


Figure 26: Time path of the cumulative profits

Due to the different profit margins—resulting from myopic profit maximization that is the basis for price calculation—the use of the absolute value of the cumulated profits is not appropriate. Therefore, the second company's share of the total cumulated profits is used for evaluation purposes. The measure is calculated as $\left(\dfrac{cum.profits_2}{\sum_{i=1}^{2} cum.profits_i}\right)$. The first graph in

Figure 27 shows, that for this measure the initial disadvantage of the second company rises with increasing demand elasticity, but also its chance of gaining an advantage rises.

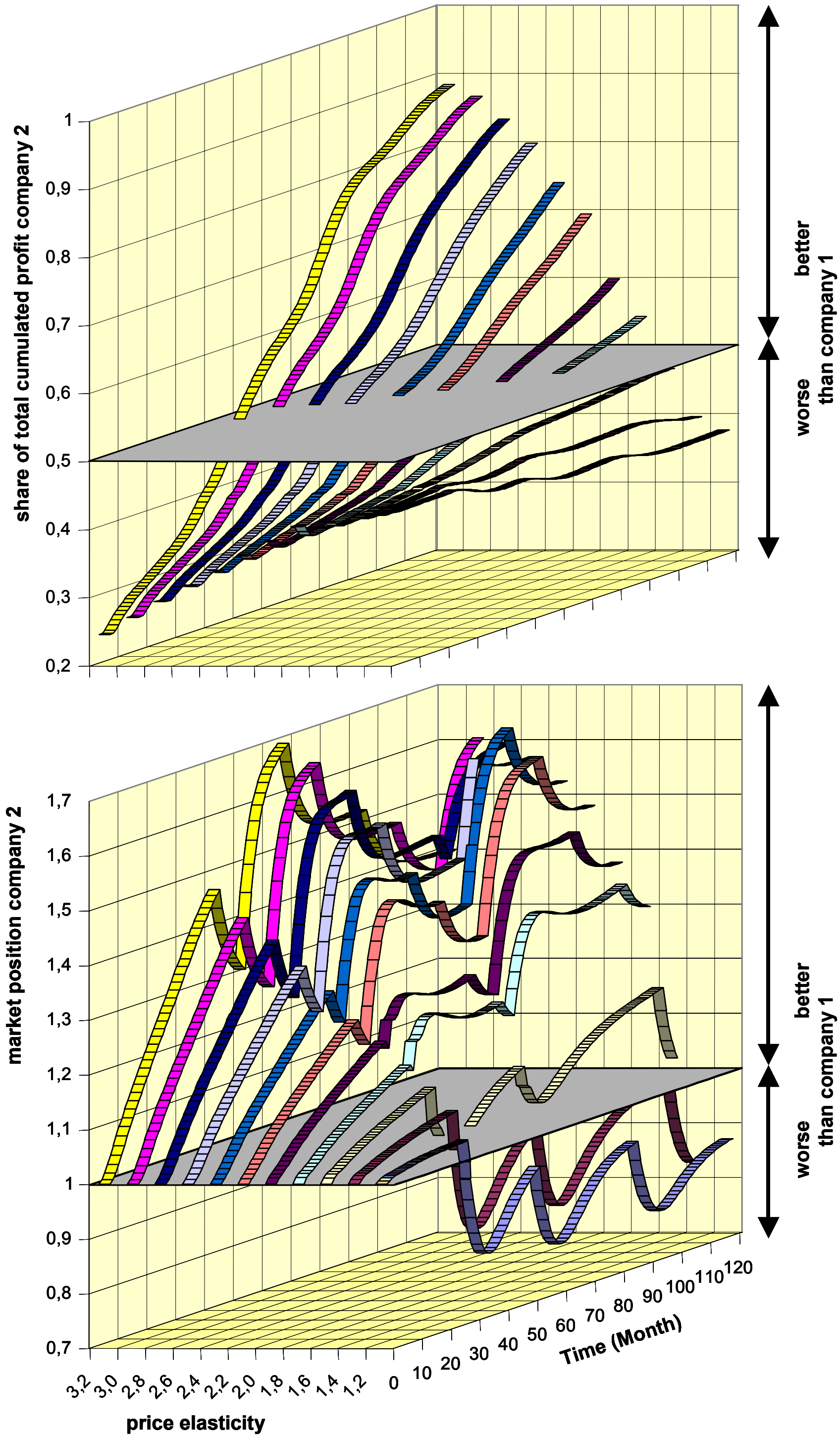


Figure 27: Impact of demand elasticity on the second company's share of cumulated profits

In the case of lower demand elasticities ($\varepsilon > -1.7$) firm 2 can not make up the initial disadvantage during the whole simulation, for demand elasticities ($\varepsilon > -1.4$) the cumulated profits ratio even deteriorate over the simulation. Considering the market position the picture is similar. For demand elasticities greater –1.6 the penetrations strategy leads to a loss in the market position over the long run. Although the introduction of the successive product generations leads to improvements of the market position, these improvements are only temporarily.

General recommendations for pricing strategies are not feasible in such complex and dynamic environments. The specific structures like, competitive situation, demand elasticity, or strategies followed by the competitors have to be taken into account. Recommendations only can be given in the context of the specific situation. Furthermore the evaluation of strategies depends on the objectives of a company. If a firm wants to enhance its sales value or the market share, the strategy of penetration pricing is the superior one. Viewing cumulative profits and the readiness for market entry as prime objectives, the strategy of skimming prices is the best. However, these recommendations hold only for high demand elasticities. Furthermore, the model does not consider price reactions of competitors. The evaluation of improved strategic behavior would become even more difficult. The outcome and the choice of a particular strategy depend on many factors that influence the diffusion process. The dynamics and the complexity of the structures make it almost unfeasible to find optimal solutions. Improvements of the system behavior gained through a better understanding, even if they are incremental, are steps in the right direction.

4. Implications for Management

The models discussed throughout this paper show that effective management of the processes of R&D, technological innovations and the diffusion of new products is a demanding task. Treating the different stages of innovation processes as separate and distinct phases is inadequate. Due to the complexity and the dynamics of the system, tools which enhance insights and learning in and about the systems under investigation are required. Investigations of innovations dynamics based on the System Dynamics approach are most promising. Neither optimal solutions nor generally valid solutions could be found, only tendencies or directions can be deduced. Optimization approaches, which are discussed in literature, e.g., to solve the problem of „the right“ pricing strategy, are inapplicable. The model must fit the unique characteristics of the problem under investigation.

The series of models presented here are designed in a modular fashion. They offer the flexibility to be adapted to different types of innovations, to different structures, initial conditions and situations. The models provide the opportunity to investigate courses of action in the setting of a management laboratory. In the real world already a few variables are enough to cause a complete misperception of a decision situation (Sterman 1989, 1994). Models allow to investigate different strategies and to learn in a virtual reality. They emphasize the process of learning in developing a strategy rather than the final result. The purpose of effective planning in a complex system like the management of innovation processes is not to produce plans; the planning process should change the mental models of the decision makers. These kinds of models work as catalysts and clarify complex internal images. They demonstrate how action and reaction or cause and effect fall apart and play together. Adequately used, these models provide a better understanding of the problem under investigation; they allow a faster reaction to market developments and the achievement of decisive competitive advantages.

Notes

[1] There is a wide range of literature reporting on success and failure rates, partly—depending on the industry—with different results. However, the numbers reported by Mansfield et al. (1981) and included in Figure 1 can still be seen as representative.

[2] These are the cost of R&D, cost of setting new or changed manufacturing processes, and cost of marketing activities like advertising campaigns for a new product. The innovation costs of the second and third stage do not consider the cost of regular production. They concentrate on the cost related to activities necessary for the product introduction like preparation and adjustment of machines for production start, or advertisement campaigns in the early phases of the new product introduction.

[3] The large shaded area at the right highlights the coarse structure of the model. The elements highlighted at the left and in the middle, are structures that will be included in the model versions discussed later in this article.

[4] For reasons of simplicity, the time subscript $_{(t)}$ is omitted in the following discussion of the innovation diffusion models.

[5] Easingwood/Mahajan/Muller (1983) used a similar way to model different influences of social pressure in imitator's purchasing behavior.

[6] Sales data were available from various sources in literature and checked for consistency. However, some of the documented data are estimations (see e.g. Stiller 1995, Meieran 1996).

[7] The technical capability of the different Intel microprocessor generations can be measured e.g., by the iCOMP index. (See e.g., http://www.ideasinternational.com/benchmark/intel/intel.html). Price development is based on various sources (e.g. Stiller 1995).

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