Management Science

The Effect of Incentive Schemes and Organizational Arrangements on the New Product Development Process

Martin Natter, Andreas Mild, Markus Feurstein, Georg Dorffner, Alfred Taudes,

The Effect of Incentive Schemes and Organizational Arrangements on the New Product Development Process

Martin Natter • Andreas Mild • Markus Feurstein • Georg Dorffner • Alfred Taudes

Department of Production Management, Vienna University of Economics and Business Administration, Pappenheimgasse 35/3/5, A-1200, Vienna, Austria
Department of Production Management, Vienna University of Economics and Business Administration, Pappenheimgasse 35/3/5, A-1200, Vienna, Austria
Department of Production Management, Vienna University of Economics and Business Administration, Pappenheimgasse 35/3/5, A-1200, Vienna, Austria
Department of Medical Cybernetics and Artificial Intelligence, University of Vienna, Freyung 6/2, A-1010, Vienna, Austria
Department of Production Management, Vienna University of Economics and Business Administration, Pappenheimgasse 35/3/5, A-1200, Vienna, Austria
martin.natter@wu-wien.ac.at • andreas.mild@wu-wien.ac.at • markus.feurstein@wu-wien.ac.at
georg@ai.univie.ac.at • alfred.taudes@wu-wien.ac.at

This paper proposes a new model for studying the new product development process in an artificial environment. We show how connectionist models can be used to simulate the adaptive nature of agents' learning exhibiting similar behavior as practically experienced learning curves. We study the impact of incentive schemes (local, hybrid, and global) on the new product development process for different types of organizations. Sequential organizational structures are compared to two different types of team-based organizations, incorporating methods of quality function deployment such as the house of quality. A key finding of this analysis is that the firms' organizational structure and agents' incentive system significantly interact. We show that the house of quality is less affected by the incentive scheme than firms using a trial and error approach. This becomes an important factor for new product success when the agents' performance measures are conflicting.
(*New Product Development; Incentive Schemes; Neural Networks; Agent-Based Simulation; House of Quality; Marketing-Production Interfaces*)

1. Introduction

New product decisions have significant strategic implications that determine the future of a business and involve several functional areas within an organization. Successful products must satisfy a range of constraints. The knowledge about these originates in many parts of an organization (Simon 1991). Recent studies (Verona 1999, Dutta et al. 1999) show that the resource-based view is well-suited to explain

a firm's success in new product development. The resource-based view of the firm characterizes firms as a bundle of resources and capabilities, that are rooted in the knowledge of the individual members and the organization (Wernerfelt 1984, Hamel and Prahalad 1994). Using the resource-based view of the firm, Dutta et al. (1999) explain interfirm differences in firms' profitability in high-technology markets in terms of differences in their marketing, R&D, and

operations capabilities, as well as their interactions. In addition to the capabilities of the agents involved, the performance of the new product development process depends on the organizational capabilities (Verona 1999). An analytical treatment of the interrelationship between organizational and individual capabilities is difficult since organizations are heterogenous, complex, dynamic, nonlinear, adaptive, and evolving systems, and organizational action is a result of interactions among adaptive human or artificial agents (Carley and Gasser 1999). Furthermore, if one assumes that economic agents are boundedly rational (Simon 1944), the capacity of agents to build models and derive submodels must be bounded too, as models are built on communicated or observed data by estimating parameters and performing symbolic computations.

The contribution of computational models for investigating the impact of different organizational models and theories about adaptive agents is well accepted (Lant 1994, Carley 1995, Carley and Gasser 1999, Carley and Svoboda 1996). Carley (1995), for instance, addresses the linkage between individual learning on the basis of cognitive models of agents and models of organizational learning, on the basis of structural models as a major research question for computational and mathematical organizational theory.

To analyze a typical development process where knowledge is distributed across different departments and persons, we use a computational model of distinct artificial agents that are based on connectionist models. Thus, contrary to many previous attempts to model adaptive behavior in economics, the focus is on a somewhat realistic implementation of a rough cognitive model. Since the choice of the agents' complexity has an impact on the outcome of such models, we carefully analyze such effects on generalizability of knowledge by means of an extensive virtual experiment. We study the impact of incentive schemes on the new product development process for different types of organizations. Sequential organizational structures (SEQ) are compared to two different types of team-based organizations. We analyze the House of Quality (HoQ) (Hauser and Clausing 1988), that supports interfunctional coordination and communication, and compare it to firms that do not employ methods of quality function deployment. Although there is some empirical evidence (Hauser 1993) of successful implementations of the HoQ for new product development, it is unclear under which circumstances it is appropriate. This is of high practical relevance, since its implementation causes considerable costs. In contrast to the coordinated search of the HoQ firms, the other team-based firms generate new product alternatives by a trial and error (T & E) search procedure. To determine strengths and weaknesses of the different search strategies, product assessment methods, and incentive schemes, we define several performance measures. In a virtual experiment, we consider different levels of product complexity, agent complexity, team size, and learning speed.

This paper is structured as follows: Section 2 reviews the related literature. In §3, we define the model environment. Section 4 explains the structure of the agents and motivates the use of connectionist models. The search for new products and their evaluation are described in §5. In §6, we formulate our propositions and describe the virtual experiment. The results, presented in §7, are discussed in §8.

2. Related Literature

Shorter life cycles, increased competition, and product complexity in today´s high-technology markets have put emphasis on the strategic importance of knowledge management within a firm (Nonaka and Takeuchi 1995, Hamel and Prahalad 1994). Lawrence and Lorsch (1967) find that the more complex the environment, the more differentiated the knowledge must be, and the stronger the need for high-bandwidth communication and nonhierarchical coordination.

A number of empirical works indicate the importance of the knowledge integration view. Clark and Fujimoto (1990) show that in the 1980s, Japanese car manufacturers who used multifunctional teams coordinated by a high-profile project manager outperformed the more loosely coupled, sequentially organized European and American competitors, both in terms of development time and product quality.

A study by Song and Parry (1997), which surveyed 788 new product developments in Japan, confirms this finding. Similarly, Ayers et al. (1997) find that the success of a new product increases with the intensity of communication between marketing and R&D.

Organizations, however, are often made up of people who represent different functional areas that have different goals and performance requirements. Production's primary objective, for instance, is to meet product specifications at lowest possible cost, whereas marketing managers aim to achieve a certain level of profits or market share (Montoya-Weiss and Calantone 1999). Organizations influence the behavior of their members via an incentive system to reach organizational objectives.

When an organization consists of distributed agents, the knowledge within an organization is distributed, too. Since economic agents are boundedly rational and have a limited capacity for computation, the assumption that the agents are not optimizing but looking for a satisfying solution from a reduced set of alternatives seems appropriate (Simon 1944). Searching for increasing long-term performance, the organization will even accept poorer strategies in the short-run, depending on the age of the organization. Based on this rationale, Carley and Svoboda (1996) formulate the ORGAHEAD model of organizational learning that allows for individual learning as well as for organizational change. They use simulated annealing to mimic the organization's search for better structures. The model allows for organizational adaption by firing, hiring, retasking (access to information), and reassigning (changing the report structure) members. Carley and Svoboda find that organizational performance depends much more on individual learning than on organizational structure. Furthermore, most organizations moved toward some form of hierarchy.

A few authors have used neural networks for modeling economic agents in the past. Most notably, the work by Beltratti et al. (1996) demonstrates the viability of the approach in modeling phenomena in the financial markets. Luna (forthcoming) provides a model of institutional learning using neural networks.

3. The Environment

Figure 1 gives an overview about the environment and the product structure in our model. Production processes X (at the bottom of Figure 1) determine costs (C) and the technical features Y of a product. Customers only view the attributes Z of the product, whose value is influenced by the technical features Y. The market share (MS) of the product depends on both the attributes of the product, and those of the competitors. The return of a product in a period is determined by its price, market share, costs, and the market volume of that period. Finally, the life-cycle return (at the top of Figure 1) is calculated as the sum of returns over the whole life cycle.

The production function (firm-specific indices are omitted in this section unless necessary for better readability) $X \to Y$ is captured by the following relationship: $Y = 1/(1 + e^{-AX})$, with A as a matrix of the production function describing fundamental technical relationships. A is the same for all organizations under consideration. The matrix A is used in our simulation to control the interfeature dependency of technical features. Thus, relationships such as the top speed of a car and its fuel consumption can be modeled.

As compared to classical microeconomic production functions such as Cobb-Douglas, our production function has the advantage that negative correlations

Figure 1   Structure of the Environment
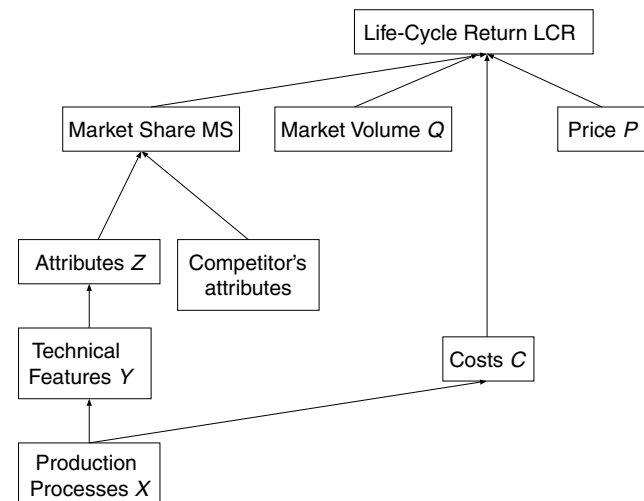
between technical features **Y** are allowed (like in the example given by Hauser and Clausing 1988).

Costs of production are a linear function of **X**, with **c** as the vector of costs: $C = \mathbf{c}^\mathbf{T}\mathbf{X}$. The vector **c** is constant in time and the same for all organizations with c_i as the cost of a single production process i. To map technical features **Y** to product attributes **Z** as perceived by the customer, a nonlinear function, implemented as a two-layer neural network with sigmoid transfer function, is used.

In this environment, firms simultaneously develop products and compete on the same market. Thus, attractiveness of a product is perceived relative to the attractiveness of all products on the market. The attractiveness of a product is a function of the product position relative to an ideal point, $\mathbf{Z}^*$. We model the distance of the product offering to the ideal point as a weighted Euclidean distance (Shocker and Srinivasan 1979): $f(\mathbf{Z}) = 1 - ((\mathbf{Z}^* - \mathbf{Z})\mathbf{W}(\mathbf{Z}^* - \mathbf{Z})^\mathbf{T})/(\mathbf{Z}^*\mathbf{W}\mathbf{Z}^{*\mathbf{T}})$, with **W** representing a diagonal matrix whose diagonal elements w_{ii} denote the weights consumers place on attribute i. The *MS* of a product i is calculated by comparing the product's attractiveness $f(\mathbf{Z_i})$ to the sum of attractiveness of all products $1, .., J$ in the market: $MS_i = f(\mathbf{Z_i})/\sum_{j=1}^{J} f(\mathbf{Z_j})$.

Life-cycle (*LC*) effects are modeled by the classical Bass model (Bass 1969), which finds strong empirical support (Sultan et al. 1990). With only three parameters (rate of innovators (p), rate of imitators (q), market potential (Q)), the sales quantity of each period is determined:

$$Q(t) = Q\left(\frac{p(p+q)^2 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^2}\right). \qquad (1)$$

The life-cycle return (*LCR*) for each firm can then be calculated as the sum of profits over all periods, $t = 1, ..., T$: $LCR = \sum_{t=1}^{T} \pi(t)$, with $\pi(t) = MS\ Q(t)(P - C)$, where P denotes the price of the product and $Q(t)$ the market volume.

4. Agent Modeling with Neural Networks

In this study, two kinds of agents were used, a marketing and a production agent, consisting of several neural networks. The production agent builds models on the relationships between production processes and technical product features. It also has to learn the relationship between production processes and costs. The marketing agent learns the relationship between technical product features and customer perceptions as well as the relationship between perceptions and attractiveness of the product perceptions. However, to search for new products and to enable the communication between the agents, inverse relationships must be also learned, since agents not only have to know about the effects of design decisions, but also how to reach good results with specific designs.

Starting without any prior knowledge about the environment, the agents observe a limited number of prototypes developed and used for a market study. Once a prototype is built, the real costs, technical features, and customer perceptions for this prototype are known. These examples then can be used by the agents to build and improve their knowledge base.

The main motivation behind our model for agent performance and learning is to capture some major aspects of human learning and performance using a somewhat realistic implementation of a rough cognitive model.

A number of authors have put forward the importance of modeling cognition in economic agents based on theories about human cognition (Carley et al. 1998). A significant part of research in agent-based simulation resorts to evolutionary algorithms to implement the adaptiveness of the involved agents (Tesfatsion 1995). While such models can reflect interesting aspects of a developing economy over several generations of agents, one must be critical toward seeing evolutionary algorithms as the main means for modeling learning (Chattoe 1998). Especially when it comes to the adaptiveness of single agents within their lifespan, genetic algorithms—although applied in many such cases (Marengo 1996)—at best can be seen as a search or optimization algorithm to yield a fit architecture given an environment. They become rather unrealistic when it comes to expressing the power and limits of human learning.

A major goal of agent-based simulations is to demonstrate the behavior of complex systems guided by boundedly rational agents. This aspect implies the

need for explicitly assuming some realistic cognitive function of the agents (Arthur et al. 1997). Given that, bounded rationality can be seen as rooted in at least three different phenomena: (1) One can assume that each agent still behaves rationally, meaning that it attempts to optimize a given utility function and always acts accordingly, but that the knowledge about this utility function is limited (bounded knowledge). (2) One can assume that the agent acts fully rationally, as in neoclassical approaches, but that time and other resources are limited, and the agent thus must resort to a suboptimal solution (bounded computational ability). (3) One can explicitly assume irrationality in that, guided, for instance, by a random process, it is also permitted to act counter to what would result from optimizing a utility function.

It is the first two aspects that we consider in this paper. By recognizing that knowledge and learning is limited for humans, and modeling this accordingly, we achieve a means of describing bounded rationality.

Nonaka and Takeuchi (1995) have put forward a theory about the knowledge in a firm, and argued about its importance in explaining economic phenomena. A major observation by Nonaka and Takeuchi is that there are both explicit and implicit, or tacit, forms of knowledge. The latter is the result of experiential learning of humans involved in the organization. Tacit knowledge cannot be made fully explicit and thus cannot be easily transferred or copied between organizations. The emphasis on tacit knowledge as a major aspect of economic agents again focuses attention toward a realistic description of adaptive cognitive behavior.

Given these motivations we decided to put a strong emphasis on how to model the behavior of single agents involved in the overall model of the firm. Natural candidates from cognitive science to model several of the aspects mentioned above are neural networks, or as they are also called, connectionist models of cognitive behavior. We chose the most simple form—a feed-forward neural network designed to learn the desired behavior of an agent as an unknown nonlinear function.

Connectionist models are known to be able to imitate the process of learning by doing, or learning by experience (McClelland and Rumelhart 1986, Hanson

and Burr 1990). Thus, they can be seen as a rough model of long-time learning as exhibited by humans.

Connectionist models are also known to depend on experience and the (statistical) distribution of data observed during learning. In other words, performance is limited to the discoverable structure provided by the training data. This reflects the above-mentioned aspect of bounded knowledge, which can result in bounded rationality even if all decisions are made as a deterministic evaluation of a utility function. In contrast to many evolutionary models, neural networks do not arrive at the most optimal, best fitted solution, but at a solution that mimics the limits of what humans learn through experience.

In multilayer perceptrons, the resulting "knowledge" is said to be "distributed" (over weights and hidden units), and thus is not easily accessible in categorical terms, reflecting the notion of tacit knowledge (Dorffner 1997). What a neural network has learned is (a) not directly transferable to another agent, and (b) more fine grained and richer than what can be expressed in concepts and rules (i.e., language). This is one of the major arguments of connectionism (Smolensky 1988) that the models can explain "subsymbolic" as opposed to merely "symbolic" knowledge.

It should be mentioned that by using neural networks, only long-term learning and knowledge is being modeled. This should not be confused with an agent's ability to consciously apply rules, textbook knowledge, strategies, and so on. Therefore, the neural network in our overall model reflects only the long-term expertise of an agent, given past experience, to achieve a solution in its domain by approximating the unknown function.

The basic task of the production agent is to learn the nonlinear relationship $\widehat{X} = f(\widehat{Y})$ between required technical features $\widehat{Y}$ and production processes $\widehat{X}$. This is done through a multilayer perceptron N_X with one hidden layer (see Figure 2). However, the targets for $\widehat{X}$ are unknown. Instead they are implicitly specified by a given nonlinear function $Y = g(\widehat{X})$ between the production processes and the product attributes $\widehat{Y}$. In other words, the agent (network N_X) must learn the *inverse* of a prespecified function g. This is a problem that is well known in reinforcement learning and

Figure 2   Network Architecture for the Inverse Production Function
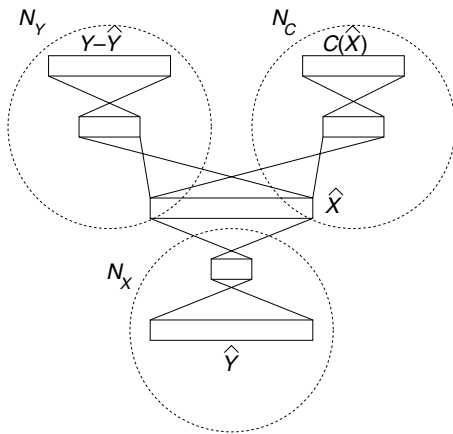
control theory. For instance, the task of controlling an industrial process can be viewed as the same problem: to learn the inverse of an unknown function (in that case, the function from the control parameters to the observed measurements of the process). A common solution to this problem is to use another neural network to first learn the unknown function (system identification), and then use this network to back-propagate errors to the actual target network learning the inverse.

This approach was adopted for the production agent. Another multilayer perceptron, N_Y, is used to learn the unknown, but externally given, function g. Network N_X can then be trained by calculating the error between the output of N_Y, $\mathbf{Y}$ (i.e., the resulting technical features), with the required technical features $\widehat{\mathbf{Y}}$, and propagating this error back all the way through network N_Y to obtain an error vector for network N_X.

Learning to suggest an appropriate set of production processes, $\widehat{\mathbf{X}}$, however, is not the only task of the production agent. In addition, the agent should attempt to minimize the costs of the product to be suggested. Therefore, another function $C(\widehat{\mathbf{X}})$ was introduced, modeling the costs of a product depending on the processes $\widehat{\mathbf{X}}$. A third multilayer perceptron, N_C, was used to permit the agent to learn that function, as well. Now the goal is to output a vector $\widehat{\mathbf{X}}$ that minimizes costs and the resulting $\mathbf{Y}$, which is as close as possible to the requests $\widehat{\mathbf{Y}}$. To achieve this, the output of N_C is added to the error term for network N_X.

In terms of what is modeled by the neural networks, the components of the production agent can be interpreted as follows. The networks N_Y and N_C constitute the agent's knowledge about how a given set of production processes lead to a final product and what its costs would be. These networks represent a kind of general knowledge about production, whereas N_X represents expertise to turn requests into an optimal product. All multilayer perceptrons consist of hidden units and output units with sigmoid activation functions. For learning, we used a scaled version of the conjugate gradient optimization (SCG) algorithm (Bishop 1998). While most connectionist models use standard backpropagation (steepest descent) as learning algorithm, we chose SCG for reasons of better performance. The main characteristics of the learning algorithm (i.e., it is based on gradient information) is preserved. Thus the resulting solutions are still valid in cognitive terms.

The marketing agent is modeled in a fashion similar to the production agent. It consists of two multilayer perceptrons designed to learn the functions $\mathbf{Z} = G(\mathbf{Y})$ between product features $\mathbf{Y}$ and product attributes $\mathbf{Z}$, as well as between product attributes and attractiveness $f(\mathbf{Z})$. Function $\mathbf{Y} = F(\mathbf{Z})$ has to be learned, where F is the inverse of function G. The properties of the networks and of learning are analogous to the production agent.

5. Organization of the Search for New Products

Figure 3 reflects the structure of alternative ways of organizing the search for new products. At the top level, we distinguish between sequential and team-based approaches. The team-based search can be organized in various ways, depending on the generation of new product candidates (HoQ, T & E) and their evaluation. Evaluation depends on the incentive system used (global, local, or mixed incentives) and the evaluation method itself (greedy or simulated annealing). In the following, we describe these approaches in more detail.

Figure 3   Organization of the Search for New Products
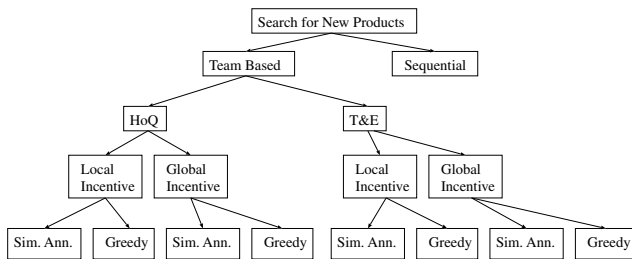
5.1. Sequential Search

We implement one possible organizational design for the new product development process as a sequential organizational structure, where one agent passes the results of its own computations to the subordinate one. We model this situation in that the marketing agent tries to formulate the technical features for its favorite product (i.e., an optimal product in terms of expected sales). The marketing agent passes the information to the production agent, which then strives to find a suitable production process to build the product at minimal cost (i.e., for given target features Y, it has to find a realization of X that results in Y at lowest possible costs).

5.2. Team-Based Search

Marschak and Radner (1972) claim to solve the problem of decentralized decision-making by introducing team theory, which is based on the use of decision rules and information structure within the organization. They assumed that all members have the same objective function leading to solidarity. However, practical experience shows that individuals within an organization are often driven by opportunism (Albach 1989). We model opportunistic behavior in applying Simon´s concept of bounded rationality. Agents apply their individual incentive system to calculate expected outcomes of their decisions, and to try to improve these outcomes. Thus, in the case of team-based new product development, agents, while continuously adapting their individual representations of the world, have to decide together about new product candidates and, then, how to evaluate possible candidates for new products.

In the search for possible candidates, we use a coordinated search procedure, viz., the House of Quality,

and compare it to a trial and error search. When the HoQ is used, agents change the previous products with respect to a potential improvement in terms of getting closer to the ideal product and/or lowering costs using the correlation matrices of the HoQ. T&E search, in contrast, randomly changes the previous product features. For both search procedures, the next step is the evaluation of new product candidates. To this end, agents calculate the expected performance of the candidate, and calculate their expected reward according to their individual incentive function. The final decision thus depends on the search algorithm and the incentive used. We compare two different product evaluation techniques, greedy and simulated annealing–based evaluations. While the first one only allows for an improvement of both utility functions, the second also allows for worse solutions for one or both agents with a probability depending on the life-cycle stage of the product.

5.3. Search Using the House of Quality

The House of Quality aims at finding a favorable product/process specification. It is a "kind of conceptual map that provides the means for interfunctional planning and communication" (Hauser and Clausing 1988). An application of the House of Quality in new product development is developed in Hauser (1993), who shows how a company developing spirometers could increase sales and profits while the cycle time of new product development was reduced in a highly competitive environment. As its name indicates, the interfunctional relationships are graphically depicted as a house. Its body is a matrix that contains the size and strength of interrelations between technical specifications (features) of a product plan and customer attributes of the product concept. The entries of the matrix indicate in what way (direction, strength) a change in Y affects Z. The original approach consists of four houses, linking product concept with product plan, product plan with parts design, parts design with process design, and process design with quality control measures. The entries are made based on tacit knowledge enriched with explicit knowledge and experimental data. The roof of the house contains correlations between the technical features Y.

For the analysis of our problem, we used only the first House of Quality, where the marketing and the production agents meet. In the House of Quality, we represent the connection between different technical features Y_i (some features promote other features, some features restrict each other)—the roof matrix—and the connection between technical features Y_i and product attributes Z_j—the central matrix—using the correlation $r_{i,j}^r = \text{Corr}(Y_i, Y_j)$ and $r_{i,j}^c = \text{Corr}(Y_i, Z_j)$, calculated from the prototypes available. Agents start with building a linear model of the impact of a change in $\mathbf{Z}$ on the attractiveness of the product $f(\mathbf{Z})$, (i.e., learning the relation $f(\mathbf{Z}) = \sum_i \widehat{W}_i * Z_i + \epsilon$). Second, a linear model of the impact of a change in $\mathbf{Y}$ to costs C is estimated $C(\mathbf{Y}) = \sum_i \beta_i * \mathbf{Y_i} + \epsilon$.

In our model, new product candidates are generated by changing one technical product feature Y_i. Consequently, one aims to find the most promising features in terms of increased attractiveness and reduced production costs. The technical features are assessed according to their potential contribution, $\rho(Y_i) = \sum_j r_{i,j}^c \widehat{W}_j - \widehat{C}(Y_i)$. The contribution depends on three components: (1) the correlation $r_{i,j}^c$, indicating the direction and strength of the impact of a variation of technical features on product attributes $\mathbf{Z}$, (2) the importance of an attribute $\mathbf{Z}$, W_i, and (3) the estimated cost effect, ($\widehat{C}(\mathbf{Y})$), of changing the technical feature. However, since this value ignores interfeature dependencies (changing one feature may result in the (unwanted) change of another one), a modified rating (ρ_m) is calculated: $\rho_m(Y_i) = \rho(Y_i) \sum_j r_{i,j}^r$, with $r_{i,j}^r$ representing the direction and strength of interfeature interdependence. In the case of interfeature independency, ρ_m and ρ are identical. The agents select the features to be changed proportionally to their rating (p_i): $p_i = \rho_m(Y_i) / \sum_i \rho_m(Y_i)$.

5.4. Trial and Error Search

In contrast to the above-mentioned method, agents do not build linear models when using the trial and error search. Instead, they randomly choose a Y_i to be changed. The advantage of this method, compared to the House of Quality, lies in the fact that the direction of search is not restricted. Since the environment is nonlinear, this method can avoid misrepresentations

in the form of building a linear model of a nonlinear world. Since the standard literature on the House of Quality assumes linear relationships between technical features and customer perceptions, its application becomes critical if the relation is nonlinear (e.g., U-shaped).

5.5. Evaluation of New Product Candidates

Potential new product features proposed by the HoQ and the T&E search, respectively, must be assessed and evaluated to decide about their acceptance or rejection. The organization influences their agents by means of an incentive scheme.

New products are assessed relative to products in the previous period. Agents calculate the performance of a candidate in terms of expected costs, market share, and profit. Based on these figures, the agents calculate their expected reward for a new product.

$$R_{MA} = \alpha * \frac{MS_{\text{new}} - MS_{\text{old}}}{MS_{\text{old}}} + (1 - \alpha) * GI, \qquad (2)$$

$$R_{PA} = \alpha * \frac{C_{\text{old}} - C_{\text{new}}}{C_{\text{old}}} + (1 - \alpha) * GI. \qquad (3)$$

The marketing (production) agent's incentive function R_{MA} (R_{PA}) consists of a reward for individual improvements and one for global product improvements. α denotes the share of individual profits (i.e., the relative improvements of market share (($MS_{\text{new}} - MS_{\text{old}})/MS_{\text{old}}$) for the marketing agent and the relative reduction in costs (($C_{\text{old}} - C_{\text{new}})/C_{\text{old}}$) for the production agent). Both agents receive a share of $(1 - \alpha)$ for relative improvement of expected profits representing the global incentive, GI:

$$GI = \frac{MS_{\text{new}} * (P - C_{\text{new}}) - MS_{\text{old}} * (P - C_{\text{old}})}{MS_{\text{old}} * (P - C_{\text{old}})}, \qquad (4)$$

where P denotes the price. For simplicity, the price is held fixed in our simulation. In our implementation, the agents choose one product feature Y_i and change it according to the rule $Y_i' = Y_i + \epsilon * \xi$, where ϵ is a uniformly distributed random variable in the range $\epsilon \in [-0.2, 0.2]$, and ξ is the sign (i.e., the direction of change), which is either given by the HoQ or chosen randomly in the case of T&E search. Then, each agent calculates its expected reward, based on its individual knowledge about the impact of the suggested change.

Agents calculate their expected reward on the basis of their individual knowledge, which is incomplete but increases over time. Therefore, the agents cannot be sure whether they correctly assess a specific product change. In other words, a potential product improvement might also lead to a decrease of profits and vice versa. There are two possible strategies to cope with such a situation. One could, despite the uncertainty, rely on the knowledge one has, and strictly search for better products. This is analogous to a greedy search procedure in optimization. Thus, in the case of greedy search, the agents only accept the suggested change if R_{MA} and R_{PA} are positive. Alternatively, an agent can be aware of its incomplete model of the world, and recognize a possible (long-time) positive effect of a product change, although it cannot explain it with its model. Therefore, when such a search model is considered, an inferior solution should be accepted with a certain probability. From an optimization perspective, this serves to avoid local minima. As the knowledge improves over time, this probability should be high at the beginning and decrease over time.

To model this search, we used simulated annealing, an optimization method that was first used by Kirkpatrick et al. (1982). In the case of simulated annealing search, agents always accept a suggested change if R_{MA} and R_{PA} are positive. Furthermore, an agent accepts a decrease of its reward with a certain probability. If the new reward is lower than the original one, the change is accepted with a probability of $1/(1 + e^{-\delta R/\text{Temp}})$, where δR is the decrease in payoffs for the agent, and *Temp* is a parameter that controls the cooling process allowing to escape from local minima. *Temp* is reduced during the life cycle of the product, so that in the beginning of the search inferior solutions are more likely to be accepted, and at the end only improvements are allowed (Carley and Svoboda 1996). Thus, in each period, the starting temperature is set to $Temp(t) = 0.2(T - t)$, where $(T - t)$ accounts for the remaining search time (periods). Within a period, the temperature is reduced depending on the number of evaluated new product candidates (i.e., the number of search steps). This mimics a kind of a brainstorming process. There, in a first step, proposals are often accepted even if they seem to be far away from being better, while in a second step, only good candidates are accepted.

6. Propositions and Design of the Virtual Experiment

To analyze this complex model, we test the different levels of all relevant factors in a full asymmetric factorial design. The factors for the virtual experiment are given in Table 1. Because of the number of design factors and levels ($2*5*2*2*3*3*4$), 1,440 different designs were implemented to run the simulation and estimate the main and first-order interaction effects. The simulation was written in Matlab Version 5.3, using the neural network toolbox *Netlab*, implemented by Chris Bishop and Ian Nabney, and uses the Matlab random number generator. This simulation runs under MATLAB Version 5 on a Pentium II or higher, and is available on request from the second author. The Monte Carlo study was carried out on a Linux-cluster, with 10 220-MHZ processors. The net total computing time was 96 hours.

6.1. Search Strategy
In the sequential organization, the marketing agent determines product features by applying its knowledge. Since its local incentive is to reach a high market share, it chooses the **Y**, which represents the production agent´s target without the consideration of technical interrelations, profitability, and its bounded rationality (inverse between technical features **Y** and **Z**). Team-based search methods jointly search for new technical features **Y**. The marketing agent therefore only has to evaluate the effects of technical features on product attractiveness, while the production agent calculates the expected costs. While the trial and error search procedure cannot capture technical interfeature dependency in the prod-

Table 1   Design Factors of the Virtual Experiment

Factor	Level
1) New Product search strategy	SEQ, HoQ, T&E
2) Product evaluation method	Greedy, simulated annealing
3) Incentive (α)	0, 0.25, 0.5, 0.75, 1
4) Team size (number of feature changes)	10, 20
5) Product complexity	Low, high
6) Number of prototypes available	25, 50, 100
7) Complexity of agents (hidden units)	5, 10, 15
8) Iterations(network learning)	50, 100, 200, 400

uct search, the HoQ approach explicitly uses interfeature correlations when searching the space of possible products.

PROPOSITION 1. *Team-based search strategies are expected to perform better than sequential approaches in general.*

PROPOSITION 2. *The House of Quality is expected to outperform the trial and error search when interfeature dependency is high.*

The environment consists of two distinct settings to investigate the impact of interfeature dependency. In the case of low interfeature dependency, each technical feature is dependent on a distinct subset of production processes (i.e., a low correlation between technical features).

PROPOSITION 3. *Since the space of possible new products is more restricted when using a guided search like the House of Quality, an unrestricted procedure is expected to end up in better products if time for search is sufficient and interfeature dependency is low.*

6.2. Product Evaluation Method and Incentive Schemes

When new product candidates are discussed (evaluated), teams choose products based on their incentive schemes and product evaluation methods. The incentive scheme determines the percentage of local and global performance measures. The product evaluation method allows either for strictly improving the individual payoffs (win-win situation) or for the introduction of slightly inferior products to avoid local minima.

PROPOSITION 4. *For the team-based organizations, we expect a positive influence of the share of global performance measures on life-cycle profitability.*

PROPOSITION 5. *Since the use of simulated annealing helps to avoid a deadlock in early development stages, we expect higher profits for simulated annealing than for greedy search.*

6.3. Number of Product Feature Changes

The size of the development team and the time available are important factors in real product

development processes (Cohen et al. 1996). Thus, in our simulation, the number of product features that can be changed in one period is varied to account for different sizes of development teams or available time.

PROPOSITION 6. *As the House of Quality systematically proposes the relevant features to be changed, we expect that it performs better than trial and error when time is scarce.*

PROPOSITION 7. *However, since more diverse products are considered in the trial and error search, we expect that in later periods of the life cycle, better products emerge as compared to the House of Quality.*

6.4. Learning Environment

Practical problems often show an inherent nonlinear relationship. When too simple models (e.g., linear regression) are used to estimate this relationship, estimates are typically biased. However, when the model class chosen is more complex than the real relationship, overfitting may occur. In literature, this problem is discussed under the term "bias-variance dilemma" (Geman et al. 1992). If the number of hidden units is large enough, neural networks can approximate any arbitrary nonlinear function (Hornik et al. 1989). The powerful approximation capabilities represent the major advantage of modeling artificial agents as neural networks. However, one must consider that complex models tend to overfit training data when the number of training patterns is low as compared to the number of parameters.

The complexity of agents in our model is determined by the different number of hidden units in the single intermediate layer we use. To measure the generalization capability of the agents, we use different numbers of prototypes in the design.

PROPOSITION 8. *Ceteris paribus*, *more prototypes lead to a better generalization.*

Simulations and empirical studies have shown that overfitting can also be avoided with early stopping. This is usually implemented by splitting the data into training, validation, and generalization sets. Training is stopped when the validation sample error measure starts to increase. In our simulation, we vary

the number of learning steps to control potential under-/overfitting tendencies.

PROPOSITION 9. *The number of learning steps and hidden units has a significant impact on generalization.*

6.5. Performance Measures

Estimated and real costs, as well as product attractiveness, represent the basic factors of different performance measures. Since time-to-market is one of the major factors that determine the success of new products in competitive markets, we calculate life-cycle profits for different life-cycle lengths (L): $M1_{iL} = \sum_{t=1}^{L} Q_{it} MS_{it} (P - C_{it})$. $M1$ allows us to study the effects of different search strategies (SEQ, HoQ, T&E) on life-cycle effects.

Our second measure, $M2$, is defined as the product of market share and margin of contribution: $M2_{it} = MS_{it}(P - C_{it})$. As compared to $M1$, which cumulates profits over time, for $M2$ all periods are of the same importance.

Generalization capabilities of agents can be measured as the sum of the absolute differences between real $(C, f(\mathbf{Z}))$ and estimated $(\widehat{C}, \hat{f}(\mathbf{Z}))$ costs and attractiveness: $M3_{it} = |C - \widehat{C}| + |f(\mathbf{Z}) - \hat{f}(\mathbf{Z})|$.

7. Results

## 7.1. General System Behavior

Figure 4 shows the average learning behavior of the three firms (SEQ, HoQ, T&E) over time. It can be seen that the system in general is able to improve cost as well as attractiveness of the developed products through learning and searching. As a result, the sum of profits for all firms is improved over time. This is consistent with practically experienced learning curves (Argote 1999). Further, the system gains the most benefits from learning within the first 15 periods and converges afterwards.

7.2. Testing of Propositions

To test Proposition 1, we performed a cross-comparison (Table 2) for the different organizations and life-cycle lengths. In terms of life-cycle profit ($M1$), both team-based approaches are significantly better than sequential search. Although this result is valid for the three different life-cycle lengths studied, the difference becomes higher with shorter life cycles. Within the team-based approaches, the HoQ is significantly better than the T&E approach.

Proposition 2 was tested with an ANOVA model for the team-based firms. In this analysis, the life-

Figure 4   General Learning Behavior/Improvement of Costs and Attractiveness (Error Bars Show 95% Confidence Interval)
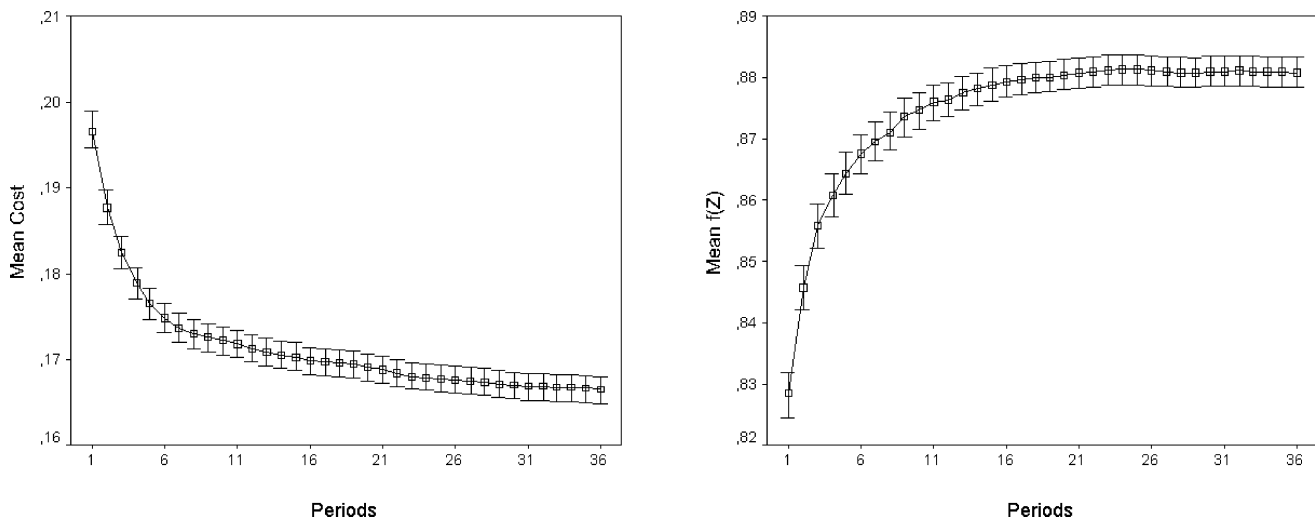
Table 2   **Cross-comparison Between Firms**

Variable	Firm	Firm	Mean Difference
$M1_1$	SEQ	HoQ	−1.23*
	SEQ	T&E	−0.97*
	T&E	HoQ	−0.26*
$M1_2$	SEQ	HoQ	−1.16*
	SEQ	T&E	−1.03*
	T&E	HoQ	−0.13*
$M1_3$	SEQ	HoQ	−1.07*
	SEQ	T&E	−0.97*
	T&E	HoQ	−0.10*

*Indicates significance at the 95% confidence level.

Table 3   **ANOVA for Proposition 4**

Factor	df	F value
Incentive(1)	4	12.04*
Sim. annealing	1	3.89*
Search strategy(2)	1	103.32*
Prototypes	1	59.67*
Product complexity	1	103.55*
Search steps	1	48.40*
Learning steps	1	50.68*
Hidden units	1	447.23*
(1)*(2)	4	17.17*

*Indicates significance at the 95% confidence level.

cycle returns $M1$ operate as the dependent variable, whereas the search strategy, product complexity, and their interactions represent the factors. This model shows significant parameters for all life-cycle lengths, supporting Proposition 2, which states that the advantage of the House of Quality over trial and error increases with more complex products (high interfeature dependency). For a life-cycle length of 1 year, the F values are 83.3 for the search strategy, 83.48 for product complexity, and 19.94 for the interaction.

Proposition 3 states that the difference between $M2$ for different search schemes should decrease over time (strong decrease when interfeature dependency is low). Figure 5 shows that for small and high product complexity the advantage of HoQ over T&E decreases over time. For low interfeature depen-

dency T&E even overtakes the HoQ in terms of $M2$, although not significantly. Proposition 3 therefore cannot be supported because of the lack of significance.

To test Proposition 4, we performed an ANOVA for the life-cycle returns $M1$ (for a life-cycle length of 1 year) of firms HoQ and T&E based on the model shown in Table 3. In addition to the main effects (search strategy, incentive, number of prototypes, product complexity, search steps, learning steps, and complexity of agents), we considered interactions between the search strategy and the incentive scheme.

Table 3 shows significance (at 95% confidence levels) for all main effects. Hence, Proposition 4 is supported by this analysis. In addition, the parameters of the interaction effect between search strategy and incentive scheme are also significant. Figure 6 visu-

Figure 5   **Returns ($M2$) for Low (Left-Hand Side) and High (Right-Hand Side) Complexity of Products (Error Bars Show 95% Confidence Interval)**
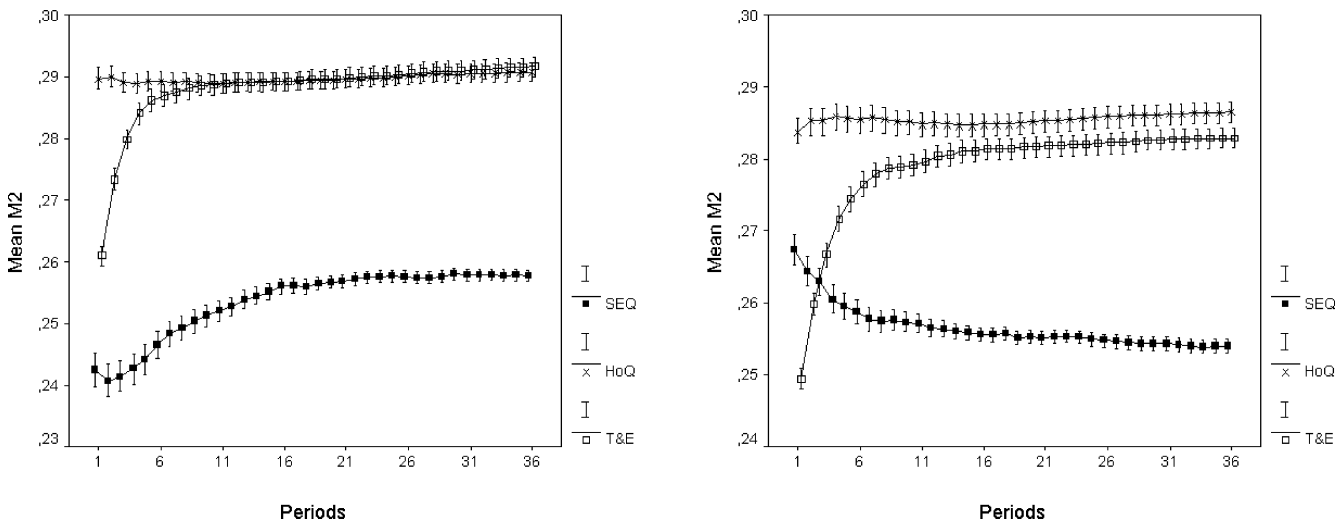
Figure 6 **Development of *M*1 for Different Incentive Schemes (Error Bars Show 95% Confidence Interval)**
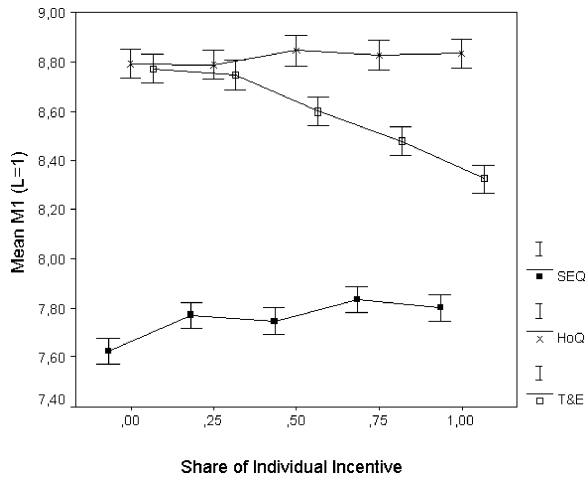
alizes that—in contrast to the HoQ—the T&E firm is significantly affected by the incentive scheme. As Figure 6 shows, the sequential firm improves its performance with increase in local incentives. Since this firm does not use incentive schemes, this can be explained by an improvement of its relative position (market share).

It is surprising that the use of the HoQ search strategy avoids a performance decrease in situations where agents follow their local incentive only. This is an important finding, since global incentive schemes are problematic in real firms because of free-rider effects (see, e.g., Olson 1971), and lower learning efficiency. These negative effects are caused by the fact that an agent's reward in a large company mainly depends on the actions of all others but only to a diminishing degree on his own performance. Further, since a learning signal hardly depends on one's own actions, it is harder to separate effects of a single process variation from the simultaneous actions of the other agents.

In the search for new products, HoQ favors technical features with a high potential for improving both market attractiveness and costs. Thus, new product proposals that are assessed by the two agents have a higher probability for a consensus. The simultaneous treatment of incentive systems and HoQ was not investigated in the previous literature. However, we find that it becomes an important factor for new product success when the performance measures (e.g., costs and market share) of the agents involved are conflicting. This significantly speeds up product improvement, resulting in good products in early stages of the life cycle. Figure 7 shows the development of *M*2 for purely global (left-hand side) and local (right-hand side) incentive schemes.

The results of testing Proposition 5 (shown in Table 3) support the stated relationship between the

Figure 7 **Development of *M*2 for Purely Global (Left-Hand Side) and Purely Local (Right-Hand Side) Incentives (Error Bars Show 95% Confidence Interval)**
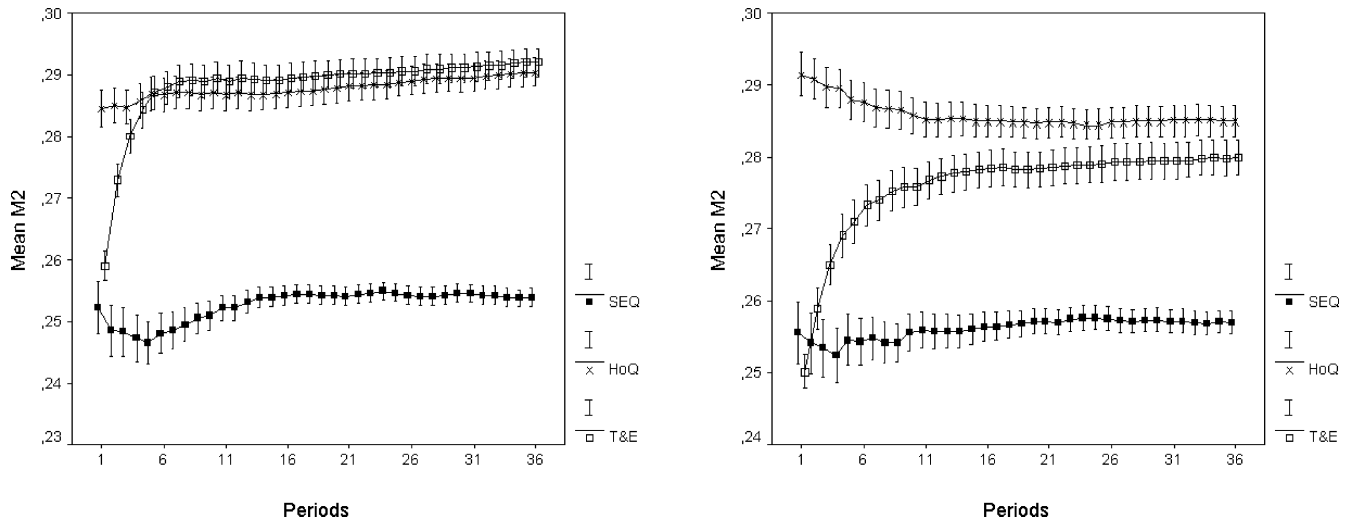
product evaluation methods and life-cycle returns (i.e., Simulated annealing leads to significantly better results than greedy assessment of product alternatives). Figure 8 shows profits ($M2$) for firms HoQ and T&E over time for simulated annealing and Greedy product evaluation. It can be noted that in early periods (Periods 1–5), both alternatives show similar progress. However, while greedy assessment (almost) gets stuck, simulated annealing helps to avoid such a deadlock.

Figure 5 demonstrates that the difference between performance of HoQ and T&E decreases over time. Proposition 6 is tested by using ANOVA for $M2$ of firms HoQ and T&E with the search strategy, time, and their interaction as factors. The search strategy (F: 935.84), time (F: 68.77), and their interaction (F: 59.62) are highly significant. The significance of the interaction effect and its sign underline the importance of the application of the HoQ when time is scarce, supporting Proposition 6.

Proposition 7 cannot be supported in general. This may be due to the restricted number of periods considered in this study. There are, however, scenarios where the stated proposition holds, namely in the cases of low complex products. Figure 5 shows that, although the difference between HoQ and T&E decreases, T&E cannot overtake HoQ when products are complex. In contrast to high feature interdepen-

Table 4 ANOVA for Propositions 8 and 9

Factor	df	F value
Hidden units(1)	2	3279.31*
Prototypes(2)	2	9292.15*
Learning steps	3	1546.17*
Time	1	12188.68*
(1)*(2)	4	1388.74*

*Indicates significance at the 95% confidence level.

dency, the T&E firm finds better products in late life-cycle stages.

Proposition 8 states that an increased number of prototypes leads to better generalization. To test Proposition 8, we perform ANOVA for $M3$ with the number of hidden units, prototypes, learning steps, and periods as factors. Proposition 8 is supported by the results (Table 4). Further, a higher number of hidden units significantly increases the generalization error, emphasizing the relevance of the agent's complexity in modeling. An increasing number of learning steps speeds up the learning process. Since we do not consider an excessive number of learning steps and periods in our design here, overfitting can only be observed because of an excessive number of hidden units. This effect is visualized in Figure 9, which reflects the relationship between the number of hidden units and the generalization error for different numbers of prototypes. Especially for the case of 15

Figure 8 A Comparison of Simulated Annealing and Greedy Decision Making
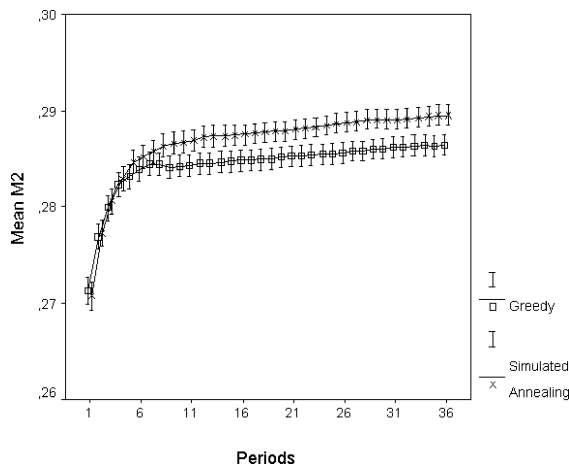
Figure 9 Error Function *M*3
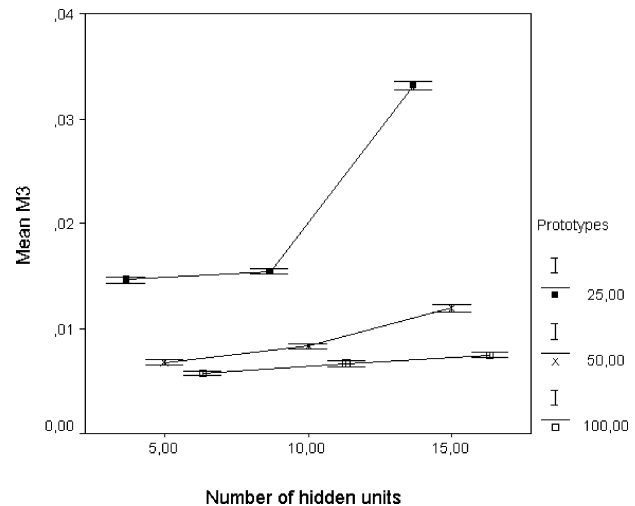
hidden units and 25 prototypes only, the agents loose their ability to properly assess product features.

8. Summary and Conclusion

This paper proposes a new model for studying the new product development process in an artificial environment. It contributes to the literature on computational organizational theory by introducing several new aspects. First, we show how connectionist models can be used to simulate the adaptive nature of agents' learning exhibiting similar behavior as practically experienced learning curves (Argote 1999). Second, we propose an operationalization of the House of Quality approach, enabling its analysis within a computational framework. Third, we offer a new application of simulated annealing within an organizational learning model, and compare its usefulness to a greedy search for new products. Our study also contributes to the literature on new product development in linking new product search models to incentive schemes.

The firms acting in this environment consist of two agents and are based on neural network models. Our analysis focuses on the organization of the product development process. We compared sequential organizational structures to two different types of team-based organizations, where one of them uses the HoQ approach. The other team organization uses the trial and error concept for new product search. The type of organizational structure determines the way new products are searched for. Potential new products must be assessed and selected from the new product candidates proposed in the first step. An organization influences this step by means of an incentive scheme. In this paper, we studied the impact of local and global incentives on the new product development process for different types of organizations. To analyze a typical development process where knowledge is distributed across different departments and persons engaged, we use a computational model of distinct artificial agents.

In our model, a marketing and a production agent build up their knowledge by learning from prototypes over time. Based on this (incomplete) knowledge and their incentives, they make new product decisions.

The speed and quality of individual knowledge creation are influenced by the richness of the information available, the complexity of the agent (number of hidden units), and the learning speed (number of learning steps per period).

To analyze this complex model, we tested the different levels of all relevant factors in a full asymmetric factorial design and defined the following performance measures: life-cycle return, profit of a firm at time t, and the agents' generalization error. Our analysis provides substantive insights about factors and their interdependency, influencing the development of new products and indicates the following managerial implications.

Organizational structure has a significant impact on the performance of new product success. Team structures are superior to sequential organizations. Team organizations can significantly benefit from the use of the House of Quality methodology. The relative advantage of the House of Quality increases with shorter life cycles, increased product complexity, and smaller development teams.

Incentive schemes are a crucial factor in the evaluation of new products, significantly influencing a firm's profitability. Increasing the part of local rewards in the incentive scheme of the agents lowers the product performance. This result is consistent with human experiments (Shi et al. 1994). A key finding of this analysis is that the firm's organizational structure and agents' incentive system significantly interact. The House of Quality is less affected by the incentive scheme than the trial and error firm as new product proposals assessed by the two agents have a higher probability for a consensus. This becomes an important factor for new product success when the agents' performance measures are conflicting.

An increased number of prototypes leads to a better knowledge base of the agents improving their capabilities in assessing new product variants. However, we find that the House of Quality brings advantages even with a small number of prototypes. We show the importance of the choice of an appropriate level of the agents complexity relative to the information available.

Simulated annealing leads to significantly better results than greedy assessment of product alterna-

tives. This result suggests that new product managers can avoid deadlocks in product improvement by changing product features despite (small) expected performance decreases. However, when the knowledge about the production and marketing effects increases, they should reduce their propensity to experiment.

We have focused on the new product development process under a competitive but stable environment (i.e., production, cost, and preference functions do not change over time). However, in reality, markets and consumer preferences are dynamic, and firms can react to new circumstances by investing in new resources and capabilities (Hamel & Prahalad 1994). Since it was shown (Argote 1999) that real firms are also affected by knowledge depreciation, it would be interesting to see further research that investigates the relationship between organizational structure and new product decisions in a dynamic competitive environment. In high-technology markets, time-to-market is a critical success factor. However, since knowledge creation may be time consuming, firms have to build up knowledge in advance and often without any specific products in mind. A promising real option's–based approach to value such knowledge-creating investments can be found in Kogut & Kulatilaka (1998). An integration of such investment decisions in our model could explain interesting aspects of real firm behavior such as the concentration on core competencies or diversification strategies.

Acknowledgments

References

Albach, H. 1989. *Organisation: Mikroökonomische Theorie und ihre Anwendung*. Gabler, Wiesbaden, Germany.

Argote, L. 1999. *Organizational Learning: Creating, Retaining and Transferring Knowledge*. Kluwer.

Arthur, W. B., S. Durlauf, D. Lane. 1997. *The Economy as an Evolving Complex System II*. Addison-Wesley, Reading, MA.

Ayers, D., R. Dahlstrohm, S. J. Skinner. 1997. An exploratory investigation of organizational antecedents to new product success. *J. Marketing Res.* **34** 107–116.

Bass, F. 1969. A new product growth model for consumer durables, *Management Sci.* **15** 216–227.

Beltratti, A., S. Margarita, P. Terna. 1996. *Neural Networks for Economic and Financial Modeling*. International Thomson Computer Press, London, U.K.

Bishop, Ch. M. 1998. *Neural Networks for Pattern Recognition*. Clarendon Press, Oxford.

Carley, K. M. 1995. Computational and mathematical organization theory: perspective and directions. *Comput. Math. Organ. Theory* **1** (1) 39–56.

———, L. Gasser. 1999. Computational organization theory. G. Weiss, ed. *Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence*. MIT Press, Cambridge, MA.

———, M. J. Prietula. 1994. Computational organization theory—an introduction. K. Carley, M. J. Prietula, eds. *Computational Organization Theory*. Hillsdale, NJ.

———, D. Svoboda. 1996. Modeling organizational adaptation as a simulated annealing process. *Sociological Meth. Res.* **25**(1) 138–168.

———, M. J. Prietula, Z. Lin. 1998. Design versus cognition: the interaction of agent cognition and organizational design on organizational performance, *J. Artificial Soc. Soc. Simulation* **1**(3).

Chattoe, E. 1998. Just how (un)realistic are evolutionary algorithms as representations of social processes? *J. Artificial Soc. Soc. Simulation* **1**(3).

Clark, K. B., T. Fujimoto. 1990. The power of product integrity. *Harvard Bus. Rev.* **68** 107–118.

Cohen, M., J. Eliashberg, T. Ho. 1996. New product development: The performance and time-to-market tradeoff, *Management Sci.* **42** 173–186.

Dorffner, G. 1997. *Neural Networks and a New Artificial Intelligence* International Thomson Computer Press, London.

Dutta S., N. Narasimhan, S. Rajiv. 1999. Success in high-technology markets: is marketing capability critical? *Marketing Sci.* **18** 547–568.

Geman, S., E. Bienenstock, R. Doursat. 1992. Neural networks and the bias/variance dilemma. *Neural Comput.* **4** 1–58.

Hamel, G., C. K. Prahalad. 1994. *Competing for the Future*. Harvard Business School Press, Boston, MA.

Hanson S. J., D. J. Burr. 1990. What connectionist models learn: learning and representation in connectionist networks. *Behavioral Brain Sci.* **13** 471–518.

Hauser J. R. 1993. How puritan-bennett used the house of quality. *Sloan Management Rev.* **34** 61–70.

———, D. Clausing. 1988. The house of quality. *Harvard Bus. Rev.* 63–73.

Hornik, K., M. Stinchcombe, H. White. 1989. Multilayer feed-forward networks are universal approximators. *Neural Networks* **2** 359–366.

Kirkpatrick, S., C. D. Gelatt, Jr., M. R. Vecchi. 1982. Optimization by simulated annealing. *IBM Res. Rep. RC.*

Kogut, B., N. Kulatilaka 1998. Capabilities as real options. Working paper WP98-05, The Wharton School, University of Pennsylvania, Philadelphia, PA.

Lant, T. K. 1994. Computer simulations of organizations as experimental learning systems: implications for organization theory. K. Carley, M. J. Prietula, eds. *Computational Organization Theory.* Hillsdale, NJ.

Lawrence P. R., J. W. Lorsch. 1967. *Organization and Environment— Managing Differentiation and Integration.* Harvard Business School Press, Boston, MA.

Luna F. 2000. Computable learning, neural networks and institutions. *Internat. J. Technol. Management.* Forthcoming.

Marengo, L. 1996. Structure, competence and learning in an adaptive model of the firm. G. Dosi, F. Malerba, eds. *Organization and Strategy in the Evolution of the Enterprise.* Macmillan, London, U.K., 124–154.

Marschak, J., R. Radner. 1972. *Economic Theory of Teams.* New Haven, London, U.K.

McClelland J. L., D. E. Rumelhart. 1986. *Parallel Distributed Processing, Explorations in the Microstructure of Cognition II: Psychological and Biological Models.* MIT Press, Cambridge, MA.

Montoya-Weiss, M., R. J. Calantone. 1999. Development and implementation of a segment selection procedure for industrial product markets. *Marketing Sci.* **18** 373–395.

Nonaka, I., H. Takeuchi. 1995. *The Knowledge-Creating Company.* Oxford Univ. Press, Oxford, U.K.

Olson, M. 1971.*The Logic of Collective Choice.* Shocken, New York.

Shi, P., P. Luh, D. Kleinman. 1994. Team coordination under individual and team goals. K. Carley, M. J. Prietula, eds. *Computational Organization Theory.* Hillsdale, NJ.

Shocker, A. D., V. Srinivasan. 1979. Multi-attribute approaches for product concept evaluation and generation: a critical review. *J. Marketing Res.* **16** 159–180.

Simon, H. 1944. Decision-Making and Administrative Organization. *Public Admin. Rev.* **4** 16–31.

———. 1991. Bounded rationality and organizational learning. *Organ. Sci.* **2** 125–134.

Smolensky, P. 1988. On the proper treatment of connectionism. *Behavioral Brain Sci.* **11** 1–74.

Song X. M., M. E. Parry. 1997. The determinants of japanese new product success. *J. Marketing Res.* **34** 64–76.

Sultan, F., J. Farley, D. Lehmann. 1990. A meta-analysis of applications of diffusion models. *J. Marketing Res.* **27** 70–77.

Tesfatsion, L. 1995. How economists can get alife. L. Tesfatsion, ed. *How to Get Alife.* CSWEP Newsletter, American Economic Association 16–18.

Verona, G. A. 1999. A resource-based view of product development. *Acad. Management Rev.* **24** 132–142.

Wernerfelt, B. 1984. A resource-based view of the firm. *Strategic Management J.* **5** 171–180.