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New Product Development in the Artificial Factory

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New Product Development in the Artificial Factory

Abstract

We study the product development process in an artificial firm using two different incentive schemes (market share/production costs vs. life cycle return). In the product development process, we compare a trial and error search to the House of Quality approach. In our study, we focus on tactical decision making within a stable environment, given resources (production function) and knowledge base. The knowledge base is represented by neural networks which are trained on the basis of prototype data. This knowledge is then used in the product development process. We demonstrate, how production and marketing agents coordinate their actions in order to produce optimal products with respect to their incentive schemes. Our simulation shows that coordinating incentive schemes increase the performance of the firm. For a given incentive scheme, the House of Quality approach always outperformed the trial and error search. An interesting feature of the HoQ approach lies in the fact that product improvement is considerably faster compared to the alternative search strategy.

1 INTRODUCTION

Traditionally, microeconomics has assumed that the form of the organizational network is hierarchical, where the result of a computation is only passed to several immediate subordinates or to one agent on the next higher level, respectively. It is assumed that management has a general model of the environment and the organization and on this basis derives the decision rules for the agents. However, economics agents have a limited capacity for computation and their knowledge is limited to their field of specialization. Therefore, if the rationality of economic agents is bounded, the capacity of management to build models and derive sub-models must be bounded too, as models are built on communicated or observed data by estimating parameters and performing symbolic computations. Thus, the assumption that - also as a team - a management agent can make a total model of the firm and its environment loses its credibility in more complex situations. Furthermore, the environment must also be rather stable, so that the need for "reorganizing", i.e. determining new decision rules, does not arise too often so that the bounded rationality of management is exceeded [12].

Both requirements are often violated today. Consider the following statement from Clark and Fujimoto [4] about the complexity of consumer behavior in today's car markets: "Car buyers don't choose between brands on prices, qualities, and functions alone anymore. In order for a brand to become appealing to them, certain "soft" variables such as "urban feeling" or "high-tech feeling" have to be added." Obviously, many variables enter into the functional relationship between the purchase probability and the technical specifications of a car in a nonlinear way in such a situation, where a number of variables have equivocal meanings and are not readily encodable. It thus seems highly unlikely that someone who is not constantly and directly exposed to customers can make a meaningful model.

When important knowledge is created through daily operations and "embedded" in the employees, one must think about how this tacit knowledge can be integrated into the *organizational knowledge base* so that via *organizational learning* good organizational decisions arise.

A number of empirical works indicate the importance of the knowledge integration view. Clark and Fujimoto show that in the 80s Japanese car manufacturers that used multi-functional 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 [4]. A study by Song and Parry [14], which surveyed 788 new product developments in Japan, confirms this finding. Similarly, Ayers et al. [1] find that the success of a new product increases with the intensity

of communication between marketing and R & D. However, when R & D and marketing personnel become too close friends, the need for harmony prohibits an open discussion of conflicting arguments and consequently new product success decreases. Lawrence and Lorsch [11] compare different companies in different industries to formulate the "contingency theory of organization": the more complex the environment, the more differentiated the knowledge has to be and the stronger the need for high-band-width communication and non-hierarchical coordination.

The aim of this paper is to develop quantitative models for organizational learning in tactical planning. We focus on modeling the new product development process and demonstrate, how production and marketing agents learn to coordinate their actions in order to produce optimal products with respect to their incentive schemes. We will also show that methods of Total Quality Management (TQM) like the House of Quality [7] are coordinated search procedures for organizational learning and study under which conditions they work best (functional and institutional integration).

2 DEFINITION OF THE ENVIRONMENT

In our study, the environment consists of three major components:

- The market definition, which describes life-cycle effects and market share as a function of product attributes and price.
- The production definition, which describes how production processes map into technical product features; i.e., the production and cost function of the firm.
- The interface definition, which describes how real technical product features are related to attributes as perceived by the consumers.

Figure 1 shows the interactions in this environment. Starting without any prior knowl-

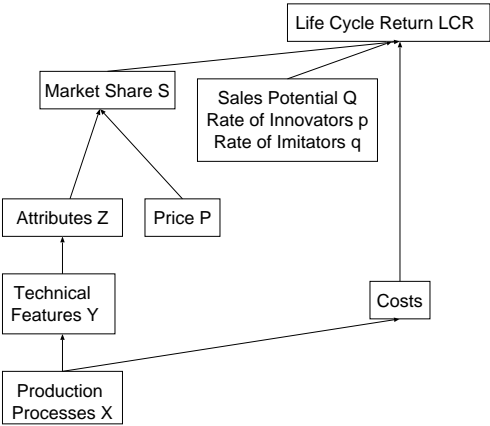


Figure 1: Structure of the environment

edge, the agents observe realizations of past actions and try to build their own model of the world. Observations of actions are realized when prototypes of a product are developed and used for a market study. Once a prototype is built, the real costs, technical characteristics and consumer preferences are known. These examples can then be used to learn their model of the world.

Market Definition

The Life Cycle Return (LCR) of a product is given by the sum of profits over all periods, $t = 1, \dots, T$:

$$LCR = \sum_{t=1}^T \pi(t) \quad (1)$$

The profit of a period is determined by the following relation:

$$\pi_i(t) = [P_i(t) - \phi_i(Y_i(t))][S_i(Z_i, P)]Q(t) \quad (2)$$

where $\pi_i(t)$ represents the profit of firm i at time t , P the price, Z the attribute vector of the product, Q the market volume, and S the firms' market share. $\phi_i(Y)$ denotes the products' costs as a function of the technical features Y .

Life Cycle (LC) effects are modeled by the classical Bass model [2] which finds strong empirical support [15]. With only three parameters (rate of innovators (p), rate of imitators (q), market potential (Q)) the sales quantity of each period is determined:

$$Q(t) = Q \left(\frac{p(p+q)^2 e^{-(p+q)t}}{(p+q e^{-(p+q)t})^2} \right) \quad (3)$$

In this life cycle model, the period with maximum demand (peak time) is given by

$$T^* = \frac{-1}{p+q} \ln\left(\frac{p}{q}\right) \quad (4)$$

Bass et al. [3] have shown that a more general version of the Bass model that includes decision variables such as prices or promotion expenditures, only slightly improves fit of empirical data. The authors show that for data where percentage changes of period-to-period values of the decision variables are approximately constant, the generalized Bass model provides almost the same fit as the Bass model that we use here.

The market share of a product, S_i , is given by

$$S_i = f(Z)g(P) \quad (5)$$

where Z denotes the attribute vector and price P .

$f(Z)$ is a function of the product position relative to the ideal point, Z^* . Following Shocker and Srinivasan [13], we model the distance of the product offering to the ideal point as a weighted Euclidean distance:

$$f_j(Z_i) = 1 - \frac{[(Z^* - Z_i)'W(Z^* - Z_i)]}{(Z^{*'}WZ^*)} \quad (6)$$

with W representing a diagonal matrix whose diagonal elements w_i denote the weights consumers place on attribute i .

$g(P)$ is a downward sloping function of price:

$$g_j(P_j) = (1 - bP_j/\rho) \quad (7)$$

with $P_j \leq \rho/b$ and ρ/b is the market's reservation price such that $0 \leq g_j(P_j) \leq 1$.

Production Environment

The production function $X \rightarrow Y$ is captured by the following nonlinear relationship:

$$Y_i = \tanh\left(\sum_{j=1}^J \beta_{ij} \tanh\left(\sum_{k=1}^K \alpha_{jk} X_k\right)\right) \quad (8)$$

As compared to classical microeconomic production functions such as Cobb-Douglas, this highly nonlinear neural network has the advantage that also negative correlations (like in the example given by Hauser and Clausing [7]) between technical features Y are allowed.

The costs of a technical feature depend on a weighted (via matrix r_{ij}) sum of the chosen processes and materials X through which the feature Y is characterized, $\sum_{i,j=1}^{I,J} r_{ij} X_i X_j$. As lowest costs can easily be achieved by setting X to zero, a penalty term for deviations from the intended features \hat{Y} is introduced. The importance of this deviation is determined by weights d . Taken together, the cost of the production agent are given by:

$$\phi_i(Y_i) = \sum_{i,j=1}^{I,J} r_{ij} X_i X_j + d_i (Y_i - \hat{Y}_i) \quad (9)$$

Marketing-Production Interactions

Attributes Z_i of a product are a weighted function of technical features Y of that attribute:

$$Z_i = \sum_{j=1} \theta_{i,j} Y_j \quad (10)$$

with $\sum \theta_{i,j} = 1$

Description of the Knowledge-Bases

The knowledge base of the production agent is represented by the weights of the neural networks of his production function and cost function views (see equations 8 and 9).

The production agent has no prior knowledge about the structure (number of hidden units, transfer functions and parameters) of the production and cost function.

In our simulation¹ the production agents knowledge base consists of a feed forward neural network with 10 hidden units, a sigmoid transfer function for the hidden units and linear transfer functions for the output units to learn the relationship between X (inputs) and Y (outputs). The real production function, on the other hand, consists of a feed forward neural network with 5 hidden units and sigmoid transfer function for hidden and output units.

For the cost function the agent uses a feed forward network with 5 hidden units, sigmoid transfer functions for the hidden and linear transfer functions for the output units; i.e., his representation is totally different from the real structure (equation 9).

Since the production agent needs to assess feasibility and costs of a new product (proposal), a second step is required: for given target features Y he has to find a realization of X which results in Y at lowest possible costs. For this second step, a specific network architecture (see Figure 2) is necessary which simultaneously learns the inverse² of function 8 and minimizes 9. The upper part of Figure 2 represents the relationships described above (left part: production function; right part: cost function). The inverse ($Y \rightarrow X$) shown in the lower part of Figure 2 is trained by an extended backpropagation procedure, feeding back deviation costs of Y and production costs $\phi(X)$. A perfectly trained network of this type yields the optimal product/process configuration for given target features. In our simulation, we used 10 hidden units (with sigmoid transfer functions) in the $Y \rightarrow X$ layer.

The marketing agent faces similar problems: he has to learn the impact of product features and price (inputs) on market share (output). For this purpose, the marketing

¹The parameter of our simulation are given in Table 1.

²To learn the inverse function is a very hard learning task and is referred to as reinforcement learning in the neural network literature [16].

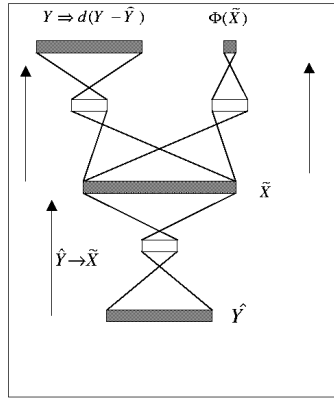


Figure 2: Network architecture for the inverse production function

agent uses a neural network with 5 hidden units and sigmoid (linear) transfer functions for the hidden (output) units. Like in the case of the production agent, the structure of the knowledge base of the marketing agent is different from the market definition.

As the technical features Y represent the common language between marketing and production agent, the marketing agent needs to learn the inverse function $(S, P) \rightarrow Y$. This forms the base for making new product proposals.

3 LEARNING AND DECISION MAKING

The marketing agent learns the expected market share of a product as a function of past realizations of product attributes, market shares, etc. The production agent learns the relationship between input factors X and technical features of the product Y on one

Table 1: Parameter of the simulation

Number of Periods T	10
Number of prototypes	64
Innovators p	0.02
Imitators q	0.2
Market Potential Q	1
Price P	0.5
Parameter b	0.8
Parameter ρ	0.4
Number of X	8
Number of Y	6
Number of Z	3

hand and which input factors to use for a given target feature Y , on the other hand, i.e., the inverse function. After having learned market reactions, the way products can be built and their production costs, the agents have to decide together which technical features and – as a result – which attributes their product should have. In contrast to individual learning, we define this process as organizational learning [8] or outer loop learning. By using team decision methods or negotiations the agents try to develop an optimal product according to their incentives. The process of coordination is cooperation or negotiation. In the case of cooperation the two agents discuss different possible sets of technical features. For each set the production agent calculates the production cost and the marketing agent calculates the market share and expected sales based on their approximations of the world. Together they are able to calculate the expected revenues and costs of producing the product - the Life Cycle Return. In a team they value different sets of technical features and choose the one that promises the highest Life Cycle Return. This method of coordination is possible if the agents can be motivated to find a solution that is optimal for the company (LCR) and if they have no different individual incentives. One way to reach such a status is to link the wage of the agents to the profit of the company. In many cases such an incentive scheme is impossible to reach. Usual benchmarks for marketing agents are sales or market shares. Production agents are often rewarded for low costs. In the case of negotiation the marketing agent tries to maximize the market share and the production agent minimizes production costs. In this setting the agents evaluate different peculiarities of the product features and accept a change only if it does not decrease their individual payoffs. So if they start with product features Y^{old} they will accept a change in design to features Y^{new} only if the new design increases market share and decreases costs. Such win-win situations are of high relevance in management practice when changes are implemented across several functional units. For both ways of negotiation (cooperation, win-win negotiation) we modeled a situation where the agents search for new products by trial and error and one where they use the House of Quality to guide their search.

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 inter-functional planning and communication" [7]. As its name indicates, these inter functional relationships are graphically depicted in 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 4 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 analyses of our problem, we used only the first House of Quality, where the marketing and the production agent 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 correlations $c_{i,j}^r = \text{Corr}(Y_i, Y_j)$ and $c_{i,j}^e = \text{Corr}(Y_i, Z_j)$ calculated for the training samples (i.e., prototypes) available. We also estimate the importance I_i of the product attributes in sales using the same samples by learning the relation

$$f(Z) = \sum_i I_i * Z_i + \epsilon \quad (11)$$

in equation (5) and the costs k_j of technical features by learning

$$\phi(Y) = \sum_i k_i * Y_i + \epsilon \quad (12)$$

in equation (9). Equations 11 and 12 are "linear" views of the world and can consequently be "learned" by linear regression models. To use the House of Quality in the search process, we calculate a rating $W(Y_i)$ of each technical feature Y_i by

$$W(Y_i) = \sum_j I_j * c_{i,j}^e - k_i \quad (13)$$

This value represents the "isolated contribution" of (Y_i) to LCR. To represent inter-feature dependencies (changing one feature may result in the (unwanted) change of another one) a modified feature value (W_m) is calculated.

$$W_m(Y_i) = W(Y_i) + \gamma \sum_{i \neq j} c_{i,j}^r * W(Y_j) \quad (14)$$

Search Models

In the process of coordination, the agents have to find a target set of technical product features Y_i that maximizes their payoffs according to their individual incentives. To model this search, we used Simulated Annealing, an optimization method that was first used by Kirkpatrick et al. [9]. In our implementation the agents choose one product feature Y_i and change it according to the rule $Y_i' = (1 - \xi) * Y_i + \xi * \beta$ where ξ is a parameter that allows to change the step width in each search (in our model, ξ is reduced during the search process) and β is uniformly distributed in the range $\beta \in [-1, 1]$.

The agents accept the change if the expected reward R' with features Y' is higher than the expected reward R for the original product. If the new reward is lower than the original one the change is accepted with a probability of

$$\frac{1}{1 + e^{\frac{R-R'}{\text{Temp}}}} \quad (15)$$

where Temp is a parameter which controls the cooling process allowing to escape from local minima. Temp is reduced during the search process - so that in the beginning of the search worse solutions are accepted and at the end only improvements are allowed.

For the two ways of negotiation, different measures of the return of a product consisting of a set of features are used.

- For cooperation the agents try to maximize LCR, i.e., $R = \text{LCR}$.
- In the case of the win-win negotiation each agent has an individual reward. R_M of the marketing agent is the expected market share S and R_P are the production costs ϕ and estimated deviations from the target features.

When utilizing House of Quality the agents also use the Model described above. They choose one feature Y_i , change it and accept the change following the methodology of Simulated Annealing. The House of Quality is used to decide which feature to change. The agents use equation 14 to weight Y_i and choose the feature to change with probability

$$p_i = \frac{W_m(Y_i)}{\sum_i W_m(Y_i)} \quad (16)$$

4 RESULTS

Table 2 and Figure 5 show average values of expected life cycle returns over 100 replications using coordinated incentives and compare them to 'real world LCR'. While columns 2 and 3 represent the results of the House of Quality (HoQ) search, columns 4 and 5 reflect the outcomes of the trial and error search (T&E). The results (see Figure 5) indicate that the agents approximation of the world is sufficient for continuous improvement. The correlation between estimated and real LCRs shows values higher than 0.9. Comparing the results of the simulation searching for new products indicates that the House of Quality approach always yields higher real world LCRs. An interesting feature of the HoQ approach lies in the fact that product improvement is considerably faster compared to the alternative search strategy (see Figures 5 and 6). The number of search steps should be regarded as the time available for discussing about new product possibilities to be introduced. This is an important finding recommending the application of the House of Quality since the number of search steps directly influences time to market.

Table 3 and Figure 6 contain the corresponding results for conflicting incentive schemes. Comparing Figures 5 and 6, we find that the absolute value of the LCRs is significantly higher with common than with conflicting incentives. When agents try to maximize their local incentives, after a certain number of iterations the agents are not able to improve LCR significantly (see Figure 6). This is due to the fact that agents accept new product proposals of the other functional unit only if they are able to improve their own (local) incentive function; i.e., when win-win situations occur. A trade off between incentives based on firms (global) performance and local incentives arises due to the fact that learning signals are more noisy for aggregate measures than for local ones. Furthermore, agents' motivation may decrease when they cannot significantly influence their performance measure. On the other hand, our simulation suggests that good overall performance can only be achieved when the individual payrolls depend on a global performance measure. A solution to this problem that takes this trade off into account is a combined incentive scheme which should also (partly) depend on the performance of the functional units interacted with in the decision process.

Table 2: Search with LCR incentive

steps	expected LCR HoQ	real LCR HoQ	expected LCR T&E	real LCR T&E
20	0.021	0.060	0.014	0.052
50	0.040	0.083	0.023	0.058
100	0.078	0.126	0.041	0.063
200	0.190	0.172	0.139	0.091
300	0.263	0.196	0.230	0.140

Tables 4, 5 and Figures 3 and 4 show average values of expected costs and market shares over 100 replications. Figure 4 shows that the marketing agent is not able to improve market share due to the veto of the production agent although improvements of market shares were still possible (however only with increased costs) and a useful step for increasing the firms profit (see Figure 5). This underlines the above mentioned trade off.

Table 3: Search with conflicting schemes

steps	expected LCR HoQ	real LCR HoQ	expected LCR T&E	real LCR T&E
20	0.032	0.060	0.046	0.021
50	0.065	0.075	0.050	0.041
100	0.108	0.089	0.054	0.069
200	0.109	0.080	0.052	0.075
300	0.111	0.083	0.053	0.075

Table 4: Expected individual payoffs with conflicting incentive schemes

steps	estimated costs HoQ	estimated costs T&E	estimated S HoQ	estimated S T&E
20	0.116	0.118	0.084	0.059
50	0.130	0.119	0.176	0.110
100	0.137	0.105	0.306	0.181
200	0.137	0.097	0.306	0.187
300	0.131	0.107	0.302	0.199

Table 5: Expected individual payoffs with common incentive (LCR)

steps	estimated costs HoQ	estimated costs (T&E)	estimated S HoQ	estimated S (T&E)
20	0.120	0.126	0.056	0.037
50	0.147	0.132	0.116	0.062
100	0.189	0.139	0.248	0.111
200	0.224	0.140	0.688	0.393
300	0.227	0.154	0.960	0.673

5 CONCLUSION

We have studied the product development process in an artificial firm using two different incentive schemes (market share/production costs vs. life cycle return). In the product development process, we compared a trial and error search to the House of Quality approach.

First, we showed that coordinating incentive schemes increase the performance of the firm. Second, for a given incentive scheme, the House of Quality approach always outperformed the trial and error search. Consequently, the integration of a coordinating incentive scheme into the House of Quality framework dominates the other search strategies investigated. An interesting feature of the HoQ approach lies in the fact that product improvement is considerably faster compared to the alternative search strategy. The number of search steps should be regarded as the time available for discussing about new product possibilities to be introduced. This is an important finding recommending the application of the House of Quality since the number of search steps directly influences time to market (cf. Cohen, Eliashberg and Ho, 1996).

In our study, we have focused on tactical decision making with a stable environment,

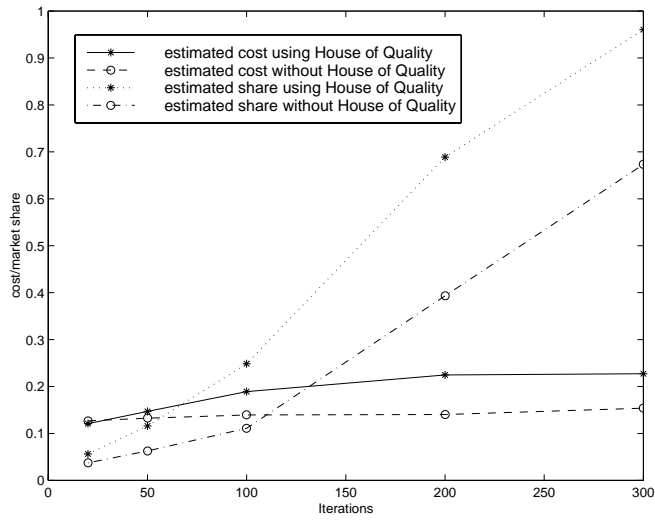


Figure 3: Expected market share and costs with common incentive scheme (LCR)

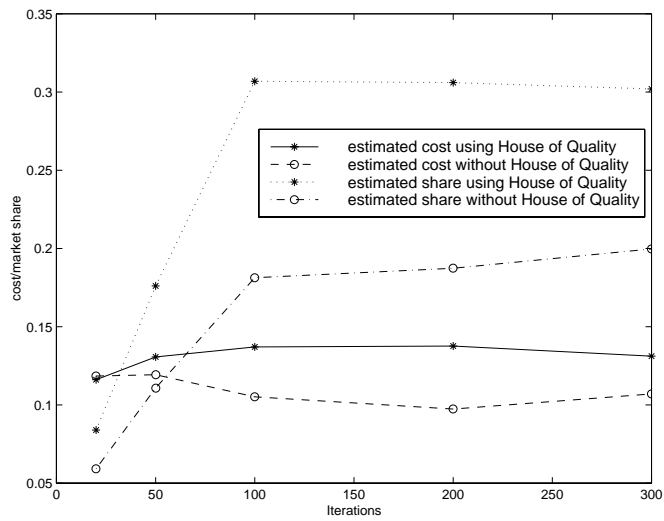


Figure 4: Expected market share and costs with conflicting incentive scheme

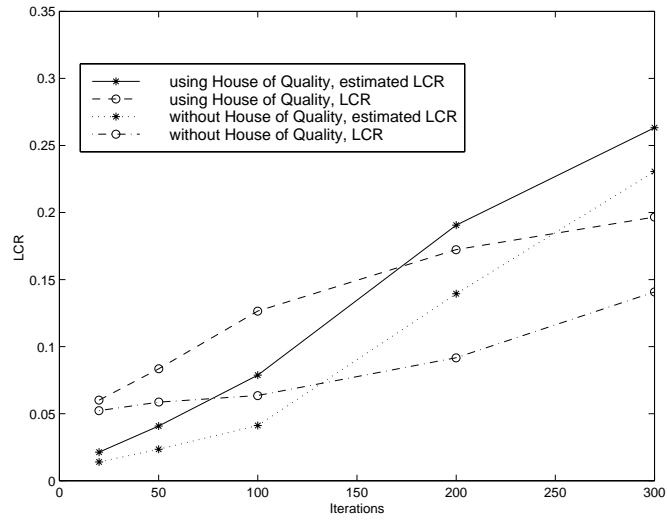


Figure 5: Expected and real LCRs with common incentives

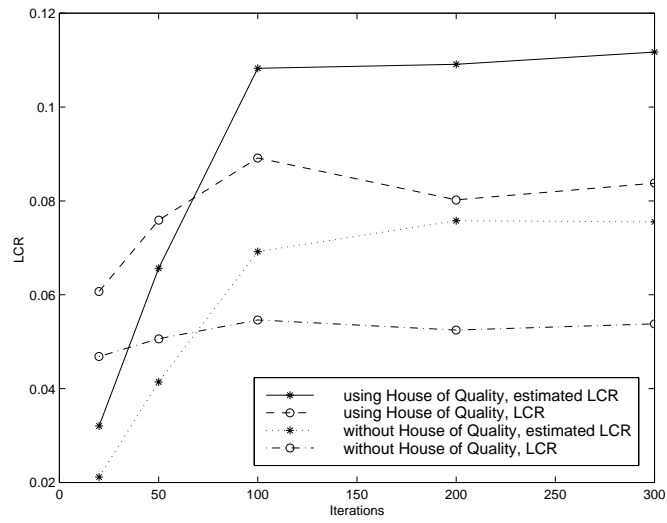


Figure 6: Expected and real LCRs with conflicting incentives

given resources (production function) and knowledge base. However, in reality, markets and consumer preferences are dynamic and firms can react to new circumstances by investing in new resources and capabilities (cf. [6]). It would be interesting to see further research that considers strategic product decisions in a dynamic competitive environment. A promising Real Options based approach to value knowledge creating investments can be found in Kogut and Kulatilaka (1998). Our analysis is restricted to a single firm with one product only.

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