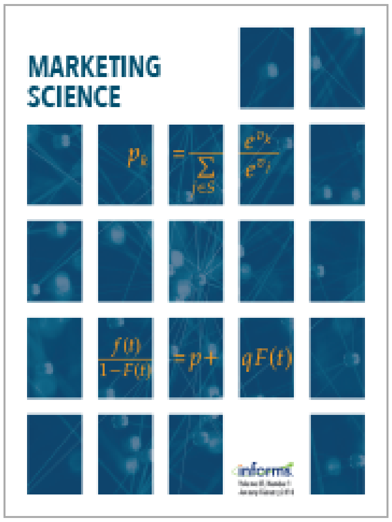

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The 2003 ISMS Practice Prize Winner

Optimizing Rhenania's Direct Marketing Business Through Dynamic Multilevel Modeling (DMLM) in a Multicatalog-Brand Environment

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We introduce Dynamic Multilevel Modeling (DMLM) to a multicatalog-brand environment to determine the optimal frequency, size, and customer segmentation of direct marketing activities. This optimization method leverages multicatalog-brand effects including the utilization of prior customer ordering behavior, maximization of customer value and customer share, and economies of scale and scope in printing and mailing. This enhancement of the original DMLM-approach is called Dynamic Multidimensional Marketing (DMDM). With DMLM alone, Rhenania, a German direct mail order company, turned its catalog mailing practices around and consequently rose from the number 5 to the number 2 market position. The DMLM approach was so effective that two major competitors could be bought out. Improvements provided by DMDM were threefold: more efficient resource allocation across all catalog brands, more accurate customer microsegmentation, and more effective reactivation. Presently, the company's target is to transform single-brand customer relationships into two- or three-brand relationships with higher revenue per customer. As a consequence, the Rhenania group's performance was decoupled from the overall market trend.

Key words: customer value analysis; database marketing; direct marketing; dynamic investment analysis; mail-order business; managerial decision making; Markov processes
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1. Introduction

Rhenania was founded in 1946 and is a medium-sized mail-order company that sells books, CDs, and related products through catalogs. In the mid-1990s, the company mailed up to 20 catalogs per year to a large number of current and prospective customers. Rhenania's customer data is stored in a proprietary database containing customer addresses, contact and buying history, and sociodemographic data. It augments this list of customers with names that it either rents from commercial address brokers (rental lists) or gains directly through campaigns in print or similar media. In the mid-1990s, Rhenania's database contained about 600,000 names, and each year, it mailed about 2,400,000 catalogs.

After the German reunification in 1990, the German economy was booming. However, this boom did not last. Unemployment has increased steadily since the early 1990s. Consequently, the propensity to consume has decreased in almost every consumer market. Thus, Rhenania has to deal with lower response rates, fewer active buyers, and lower annual sales and profits, especially after 1994.

Until 1997, Rhenania had followed the standard marketing approach to managing customer contacts and selecting profitable customers for each mailing. This traditional approach is also recommended in academic publications on direct marketing, for example, by Bult and Wansbeek (1995) or Colombo and Jiang (1999). In other words, Rhenania only sent catalogs to clients if expected revenue exceeded the total cost of the following: merchandising, order fulfillment, and the mailing itself. This strategy led to an increased profitability of single direct mail campaigns, but the longer-term consequence was a dramatic overall company downturn, because of a shrinking active customer base, declining sales, market share, and profits.

Given that promotion and mailings in particular constitute the most effective marketing mix element in the catalog mail-order industry, Rhenania decided it was necessary to rethink its overall mailing strategy. More specifically, three major issues had to be addressed (Bitran and Mondschein 1996, Elsner et al. 2003):

- How often and when should customers receive mailings over a given period (*frequency and timing of direct marketing campaigns*)?
- How many customers or customer segments in the company's database should be contacted (*size of direct marketing campaigns*)?
- Which customers should be included in which campaign (*customer segmentation*)?

As will be shown in the following sections, Rhenania was able to address these issues successfully by applying dynamic multilevel modeling (DMLM), a multilevel modeling approach for determining the optimal number, frequency, and size of direct marketing activities, as well as customer segmentation over a rolling horizon of one year. This general notion of coordinating and optimizing direct marketing contact over time has been discussed in a number of publications by direct marketing researchers and practitioners, such as Wunderman (1997), Kestnbaum et al. (1998), or Malthouse (2003). However, none offers any evidence that such an approach works, nor does anyone spell out any details. Our innovative concept not only helped turn Rhenania's mailing business around in 2001, but also DMLM enabled Rhenania to acquire Akzente and Mail Order Kaiser, which were two of Rhenania's major competitors. This led to a new challenge, namely, optimizing direct marketing activities dynamically across several catalog brands. Although this problem was new to Rhenania, it is quite common among large catalog retailers: Many mail-order companies that deal with several catalog brands face multidimensional analysis problems. For example, consider the OTTO Combined Group, the world's largest mail-order company. OTTO Combined Group serves the German full-line mail-order market with its major brands OTTO, Schwab, Witt Weiden, and Baur (see http://www.otto.com). In an interview, a top executive of the OTTO Combined Group confirmed that a substantial number of OTTO's customers order products from two, or even more, of the group's catalog brands.

In a multicatalog-brand environment like the one described above, an optimization method is needed to leverage multicatalog-brand effects. This method includes utilizing prior-customer ordering behavior across different catalog brands and exploiting the potential for maximizing customer value and customer share across those brands, as well as economies of scale and scope in printing and mailing. However, the DMLM approach was developed to optimize mailing strategies for a single catalog brand only. The modeling concept does not take into account any interdependencies across a group of catalog brands. In order to leverage these multicatalog-brand effects, a more enhanced approach had to be developed and applied simultaneously to Rhenania's catalog brands. This new approach is called dynamic multidimensional marketing (DMDM) and will be explained in more detail later.

This article is organized as follows. In §2, we review the literature on current approaches and optimization models in direct marketing. In our view, no single concept can provide answers to the three important marketing questions described earlier. For this reason, we developed the DMLM model. Section 3 provides a nontechnical description of the basic philosophy behind the DMLM approach. Section 4 conveys mathematical details of the model that helps optimize mailing strategies over a rolling horizon. The successful application of DMLM to Rhenania's customer base has been remarkable and is described in §5. However, after the acquisition of Akzente and Mail Order Kaiser in 2001, applying DMLM to Rhenania's three catalog brands separately revealed that multicatalog-brand effects were not adequately leveraged by the model. Therefore, we developed a new multidimensional approach called dynamic multidimensional marketing (DMDM). This model extension is described conceptually in §6 and mathematically in §7. The practical implications of DMDM are discussed in §8. In §9, the paper concludes with a summary, in which further issues such as transferability to other industries and the limitations of the DMLM and DMDM approaches are discussed.

2. Literature Review

Prior to developing our own model, we reviewed the relevant direct marketing literature. Several concepts aim at facilitating an appropriate decision about which customers in a company's database should be targeted. A common characteristic of these methods is that they claim to indicate the future value of catalog company customers. A classic and very common approach is to use an RFM model, in which an estimation of the likelihood of a future response is based on recency R, frequency F, and the monetary value M of past responses. Regression methods are a key technique for modeling the relationship of RFM to response (Colombo and Jiang 1999). Since response is usually measured by a *buy* or *no-buy decision*, logistic regression is used frequently (Hosmer and

Lemeshow 2000) and, particularly where many other variables are available and interactions are suspected, tree-based regression methods (e.g., AID, CHAID, CART) have proven their efficiency (Haughton and Oulabi 1993). Neural networks have been used to uncover relationships between response and behavioral, demographic, and other predictor variables (Zahavi and Levin 1995).

Another common approach to predicting the future behavior of customers is the use of direct marketing scoring models. A scoring model is defined as a data-mining model that predicts the likelihood of some behavior, based on other information available about a prospect or customer. A scoring model assigns every observation in a database a score indicating how likely someone is to engage in a particular behavior (Malthouse 2003). The functional form and estimation of scoring models have been the focus of recent research (Bult 1993; Bult and Wansbeek 1995; Zahavi and Levin 1997; Hansotia and Wang 1997; Malthouse 1999, 2001).

Customer lifetime value (CLV) analysis is a widely used concept for forecasting the development of a customer relationship. Dwyer (1989) applied the CLV concept to both customer retention and customer migration. Blattberg and Deighton (1996), as well as Berger and Nasr (1998), moved beyond simple CLV calculations by utilizing mathematical models. Building directly on this work, Pfeifer and Carraway (2000) introduced Markov chain models, which are appropriate for modeling customer relationships and migration, as well as customer retention scenarios.

So far, all of these approaches concentrate on the question as to which customer should be contacted in the *next* campaign. However, all concepts discussed so far fail to address the issues of *when* and *how often* customers should receive an offer. Campbell et al. (2001) took a first step in this direction. They developed an optimization approach, called a mail stream, aimed at selecting for each customer the most profitable sequence of several independent catalogs. One of the objectives of this model was to increase cost efficiency by preventing redundancy of catalogs being sent to customers. The model was developed by IBM and successfully applied to the firm known as Fingerhut. However, in a manner similar to that of the previously mentioned direct marketing optimization methods, only a short-term improvement in profitability was achieved, while the number of active customers, sales, and market shares continued to decrease (Campbell et al. 2001, p. 86).

Unlike all of these concepts, dynamic multilevel modeling, or DMLM (Elsner et al. 2003, Elsner 2003), does not target the short-term optimization of single direct marketing campaigns or mail streams. Instead, its aim is to find, for a given medium-term period, the optimal: (a) number of direct marketing activities, (b) size of each campaign, and (c) customer selection to increase the active customer base, sales, *and* profits. Therefore, it answers the most important direct marketing question: *When* and *how often* should *which customer* (of a given brand) receive *which offer*?

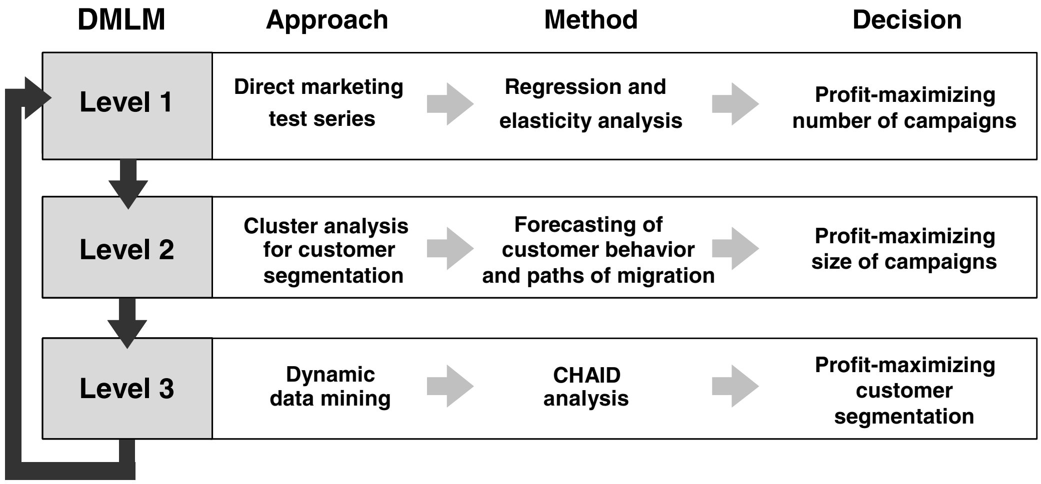
Although DMLM works on three different levels, it is still one-dimensional and considers only one catalog brand. However, many mail-order companies that deal with several catalog brands face multidimensional analysis problems. It is clear that an optimization method that addresses these multicatalog-brand effects is needed. Recognition of this fact provided the initial impetus for DMDM, an improved version of DMLM. Our paper focuses on that approach.

3. Dynamic Multilevel Modeling (DMLM)

In direct marketing practice, the ability to measure the success of each individual promotion led to a "myopic" optimization approach with a primary focus on single campaigns only. In general, optimizing the success of single campaigns such as mailings, catalogs, call center activities, etc. does not necessarily result in maximizing the overall performance of a firm measured, for example, by its annual profit. From a corporate perspective, maximizing the overall result in the medium term is more important than the short-term success of single campaigns. However, this may conflict with accounting or marketing management perspectives. A workable optimization approach toward reaching this goal clearly also requires more sophisticated modeling skills in order to limit the inherent risks.

In order to maximize profits over a certain period, it is necessary to develop a dynamic profit function with respect to the number and size of marketing campaigns. It is easy to understand that there is a considerable difference between, for example, sending out catalogs twice a year with a mail volume of 10,000 addresses each and sending monthly catalogs to 1,000,000 people. In order to solve this optimization problem, the number of campaigns n and the campaign volume v must be considered in the profit function P. Since there is a variety of address-quality criteria (i.e., accuracy and completeness of name, title, and customer profile information, such as purchase history), expected value per name varies for a direct marketing company. For example, sending catalogs to customers who have ordered very recently has a much higher expected revenue than sending the same catalog to customers who have not placed an order for several years or who have had no relationship with the company at all. Therefore, customer segmentation is needed to aggregate consumers with a similar likelihood of response.

Figure 1 Structure of Three-Level Optimization Approach to Determining Profit-Maximizing Number, Size, and Customer Segmentation of Direct Marketing Campaigns over a Certain Period



Note. Using a Rolling Horizon, DMLM considers a period (e.g., one year) to optimize the number of campaigns (Level 1), determine the size of each campaign, and reveal the absolute limit for profit-maximizing segmentation (Level 2). A data-mining process separates any possible microsegment of customers exceeding this limit (included in the next mailing) from those that should be excluded or receive a special reactivation offer (Level 3). Level 3 and Level 2 analysis are applied repeatedly and iteratively to avoid dead-weight loss of direct marketing campaigns.

Figure 1 shows the structure of this three-level optimization approach to determining the profit-maximizing number, size, and customer segmentation of direct marketing campaigns over a certain period.

To maximize the medium-term overall company result, forecasting consumer behavior is essential. In particular, it is necessary to consider how response and order size for a customer change when the individual is more or less frequently contacted by means of a company's direct marketing promotions.

In the *DMLM Level* 1 analysis, this consumer behavior is measured by the two elasticities of response rate ε_r and average order size ε_a of customer segments with respect to additional promotions. It should be mentioned that the use of elasticities is uncommon in direct marketing, although they are commonly used in marketing science. Nevertheless, it is appropriate to quantify consumer response to changes in the number of promotions. As long as additional direct marketing campaigns generate additional revenue and produce higher overall earnings, they are profitable.

In Rhenania's case, the house list was divided into three segments according to the time elapsed since the last purchase: Customers in the first segment ordered within the past 12 months, those in the second segment within the past 13 to 24 months, and those in the third segment even less recently. These segmentations conform fairly closely to the follow-up ordering behavior of reactivated customers from Segments 2 and 3. This means that customers who place an order after being temporarily inactive for at least one year have, on average, the same likelihood of reordering as the average of respective customers in Segment 1.

In two years of experimental testing and regression analysis (for a detailed description, see Elsner et al. 2003), Rhenania developed reliable elasticity coefficients for determining the profit-maximizing number and frequency of its catalogs over a period of one year.

The profit-maximizing number of campaigns n is then utilized in the *DMLM Level* 2 analysis. Here, with respect to the company's potential of customers and prospects, the profit-maximizing size of these n campaigns is determined.

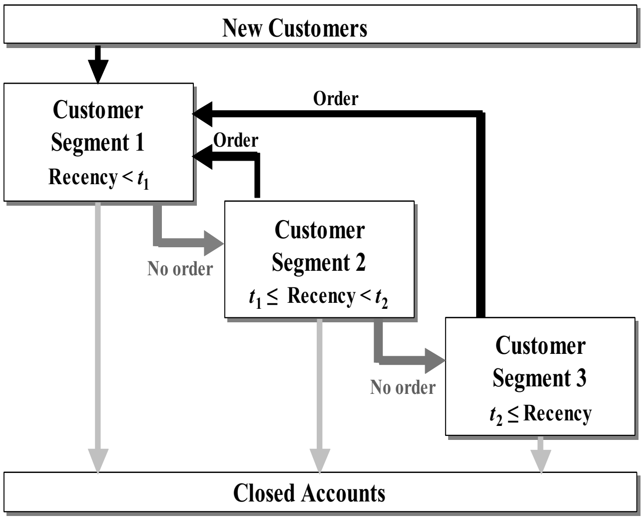
In order to handle the model complexity efficiently, we focus initially only on customer purchase recency. The main reason is that recency is a good predictor of customer response (Reinartz and Kumar 2003).

We assume a Markov-chain-like process whereby, given the stimulus of a catalog, customers will migrate from all lower segments to Segment 1 when they make a purchase (Biggs et al. 1991; Bitran and Mondschein 1996, 1997; Pfeifer and Carraway 2000).

Customers who do not order for the specified period of time will migrate from Segment 1 downward. In addition, the model takes into account the possibility that names will disappear for a variety of reasons. Among the reasons that lead to closed accounts are: inability or unwillingness to pay, returned mails because of unknown addresses, or death of customers. Furthermore, the firm periodically replenishes the customer database through list rentals and ads (Figure 2).

At Level 2 of the DMLM approach, it can be proven with straightforward mathematical modeling (see the following section), that in the medium-term, it pays even to mail to customers from Segments 2 and 3,

Figure 2 Customer Migration Between Different Segments



Note. Customers are segmented using the recency (R criteria) of the last purchase. The rate of promotion and demotion of customers depends on the response rate of each customer segment. The number of new customer accounts and accounts to be closed is assumed constant, based on the fact that empirically, these numbers do not exhibit large variations. Consequently, a fixed number of customers per campaign either buy and thus move up into customer Segment 1 or do not buy and thus either remain in their current segment or drop down into a lower customer segment (except for customer Segment 3).

who would be considered unprofitable from a traditional, short-term point of view. The DMLM approach is based on the idea that short-term losses with low-value customers can be more than adequately compensated in the medium term (e.g., a year), because the probability of future orders from a customer increases substantially after his reactivation. In addition, the company can reap economies of scale per campaign that also have to be considered in the optimization model.

In addition, we can derive analytically the threshold value for the minimum required sales per customer per segment per campaign s^*. This threshold value s^* depends on the overall number of campaigns, the expected average sales per customer of Segment 1, the response rate, and the marginal costs of marketing to the lowest customer segment. It captures the trade-off between the costs of continued promotions and the expected medium-term profitability from repeat buying. Moreover, in the optimum solution, the marginal revenue of the lowest segment to be included in the next campaign is less than the marginal cost of the promotions (see the Appendix).

At *DMLM Level* 3, a predictive model is applied to determine the profit-maximizing microsegmentation of the customer base. As will be shown in §4, we considered relatively small groups of at least 500 customers in order to establish whether these microsegments were likely to generate expected sales higher than the critical value s^*. As predictors, this analysis utilizes combinations of variables based on:

- purchase history (RFM, response, buying, returning, and payment data);
- promotion and contact history (source/origin, frequency/mode of promotions or contacts, etc.);
- behavioral data (mail-order affinity, fields of interest, market basket, etc.);
- demographic data (gender, age, income, education, title, culture, marital status, etc.);
- geographic data (country, residence, section, residential unit, housing conditions, density of population, etc.).

The particular predictive model we use is CHAID. A systematic comparison based on a CHAID analysis between the expected average sales per customer of these microsegments, built on combinations of these variables and the threshold value s^*, shows whether this particular microsegment should be promoted regularly, targeted with a special reactivation offer, or not be considered at all. This procedure yields the profit-maximizing customer microsegmentation.

The DMLM Level 3 analysis neither uses simple scoring systems nor divides up the house list arbitrarily into equal parts with regard to certain variables like RFM (which is common practice in the mail-order industry today). This data-mining approach produces a strict microsegmentation of the company's available customers so that it can maximize profits. It not only determines microsegments of the customer base that are probably better than other microsegments, but also it identifies the profit-maximizing segmentation: Each microsegment with $s = s^*$ has to be mailed in order to achieve the maximum profit!

The whole DMLM process is conceived as a decision-making process whereby the result at Level 1 can be expected to be fairly stable; Levels 3 and 2 are especially highly interdependent. Therefore, in some cases, more than one run is needed to ensure stable solutions. In Rhenania's case, DMLM Level 3 analysis revealed microsegments of inactive customers that should no longer be promoted. Those names must be excluded from the DMLM Level 2 analysis, which consequently changed the optimal size of campaigns as well as the required threshold value s^*. Nevertheless, after the DMLM decision process has been run iteratively a few times, the results converge rapidly to a stable solution with relatively marginal changes in s^* and in optimal campaign size, i.e., less than 5% within a period of one year.

4. Mathematical Details of DMLM

The DMLM approach works at three different levels. At the *first level*, elasticities of average order size $\varepsilon_a(n)$ and response rate $\varepsilon_r(n)$ are estimated by means of experimental data using multiple split runs of direct-mail test series. They are used to determine the profit-maximizing frequency, number n_{opt} of catalogs, and mailings per period.

$$\begin{aligned}&\text{Max}\;\; P(n) = n\cdot v\cdot r[\varepsilon_r(n)]\cdot a[\varepsilon_a(n)] - C(n)\\ &\text{subject to}\;\; n \le n_{\max}\\ &\qquad = \text{Min}\big(\{n_{L1}, n_{L2}, n_{L3}, \dots, n_{LI}\} \mid n_{Lt}\big).\end{aligned} \tag{1}$$

where

- a average order size
- C cost function
- L set of limitations, such as budget constraint, supply structure, production time, minimum required time interval between two campaigns, etc.
- n number of direct marketing campaigns
- $n_{\max}$ maximum number of feasible direct marketing campaigns
- n_{opt} profit-maximizing number of direct marketing campaigns
- P profit function
- r response rate
- t timing, appropriate mail dates
- v mail volume, number of names.

Derivation with regard to n yields the optimal number of campaigns n_{opt}.

$$\partial P(n)/\partial n = 0 \mid n \le n_{\max} \;\Rightarrow\; n_{\text{opt}}. \tag{2}$$

At the *second level*, a customer migration model based on a Markov-chain-like process shows how many customers are expected in each considered segment at the end of the planning horizon. The planning horizon H is measured in direct marketing campaigns with $H = [1, n_{\text{opt}}]$.

For the three-segment example, we showed in Figure 2, that the potential of each address segment for a future campaign n is:

$$\begin{aligned}v_{1n} &= v_{11} + (n-1)\,(g - d_1 - x_1) + \sum_{i=1}^{n-1} (r_2 v_{2i} + r_3 v_{3i}),\\ v_{2n} &= v_{21} + (n-1)\,(d_1 - d_2 - x_2) - \sum_{i=1}^{n-1} r_2 v_{2i},\\ v_{3n} &= v_{31} + (n-1)\,(d_2 - x_3) - \sum_{i=1}^{n-1} r_3 v_{3i}.\end{aligned} \tag{3}$$

where

- d_j demoted customers of segment j, moving to the next segment: $d_j = (1-r_j)^{n_{\text{opt}}} v_{j1}/n_{\text{opt}}$; $j = \{1, 2\}$
- g_n number of new customers gained in campaign n: $g{:=}g_1 = g_2 = \cdots = g_{n_{\text{opt}}}$.
- x_{jn} number of deleted customers from segment j leaving the house list after campaign n: $x_j{:=}x_{j1} = x_{j2} = \cdots = x_{jn_{\text{opt}}}$
- v_{jn} mail volume, number of names in segment j at the time of campaign n.

As can be shown empirically, d_j, g_n, and x_{jn} do not vary substantially over time. Therefore, assuming them to be constant can be considered a reasonable simplification. Combined with a time-series analysis to forecast the expected response rate, average order size, and number of deleted customers for each segment (we assume all to be constant for all n campaigns), the revenue and cost functions for the n_{opt} direct marketing campaigns over the entire planning horizon, can be derived. We formulate the following equations for accumulated sales S, costs C, and profit P over n mailing campaigns.

$$\begin{aligned}S(V) = {}& s_1\big(nv_{11} + n(n-1)(g - d_1 - x_1)/2\big)\\ &+ s_1\big(v_{21}\big[n - [(1-r_2)^n - 1]/(-r_2)\big]\\ &\quad + (d_1 - d_2 - x_2)\\ &\quad \cdot \big[(n-1)n/2 - n/r_2 - [(1-r_2)^n - 1]/r_2^2\big]\big)\\ &+ s_1\big(v_{31}\big[n - [(1-r_3)^n - 1]/(-r_3)\big]\\ &\quad + (d_2 - x_3)\big[(n-1)n/2 - n/r_3\\ &\quad - [(1-r_3)^n - 1]/r_3^2\big]\big)\\ &+ s_2\big(v_{21}[(1-r_2)^n - 1]/(-r_2)\\ &\quad + (d_1 - d_2 - x_2)[nr_2 - 1 + (1-r_2)^n]/r_2^2\big)\\ &+ s_3\big(v_{31}[(1-r_3)^n - 1]/(-r_3)\\ &\quad + (d_2 - x_3)[nr_3 - 1 + (1-r_3)^n]/r_3^2\big)\end{aligned} \tag{4}$$

where

- s_j average sales per customer of segment j: $s_j = r_j a_j$
- V volume, number of names contacted over the whole planning horizon: $V_{jn} = \sum_{i=1}^{n} v_{jn}$; $j = [1, 3]$.

In order to compute total sales as given in Equation (4), the number of customers in each segment, which follows from Equation (3), is multiplied by the respective expected average sales per customer.

$$C(V) = \begin{cases} c_1(V_{1n}) + n\hat{c}_1 & v = [0, v_1],\\ c_2(V_{1n} + V_{2n}) + n\hat{c}_2 & v = (v_1, v_1 + v_2],\\ c_3(V_{1n} + V_{2n} + V_{3n}) + n\hat{c}_3 & \\ & v = (v_1 + v_2, v_1 + v_2 + v_3],\end{cases}$$

$$\begin{aligned}\text{with}\quad & n\hat{c}_1 < n\hat{c}_2 = c_1(V_{1n}) + n\hat{c}_1\\ & < n\hat{c}_3 = c_2(V_{1n} + V_{2n}) + n\hat{c}_2.\end{aligned} \tag{5}$$

where

c_1 variable costs per customer if mails are sent to Segment 1 only
c_2 variable costs per customer if mails are sent to Segments 1 and 2
c_3 variable costs per customer if mails are sent to Segments 1, 2, and 3
$\hat{c}_1$ fixed costs per customer if mails are sent to Segment 1 only
$\hat{c}_2$ fixed costs per customer if mails are sent to Segments 1 and 2
$\hat{c}_3$ fixed costs per customer if mails are sent to Segments 1, 2, and 3.

$$P(V) = S(V) - C(V). \tag{6}$$

In order to evaluate whether the use of so-called low-value or inactive customers (i.e., customers in Segment 3) is appropriate so as to maximize the medium-term profit, we take the derivative of $P(V)$ with respect to V_{31}:

$$\partial P(V)/\partial(v_{31}) = 0 \iff s_1(n-\lambda) + s_3\lambda = nc_3$$
$$\text{with} \quad \lambda := [(1-r_3)^n - 1]/(-r_3). \tag{7}$$

If the response rate of Segment 3 is positive, the following condition holds:

$$1 > r_3 > 0 \iff 1 < \lambda < n. \tag{8}$$

This implies that profit can only be maximized over the entire period if address segments with expected marginal sales *lower* than their marginal costs are included in future direct marketing campaigns.[1]

Profit is maximized for given s_1, c_3, and λ:

$$s^* := s_3 = [nc_3 - s_1(n-\lambda)]/\lambda. \tag{9}$$

The value of s^* can now be calculated explicitly. This value trades off the costs of continued direct marketing activities and expected medium-run profitability. Segments in which one expects s to exceed s^* must be included in forthcoming campaigns. Hence, the profit-maximizing size of campaigns follows from the above procedure for a given customer base. Determining the optimal threshold level s^*, i.e., the minimum required average sales per customer of a specific segment per mailing, is a key factor in achieving a more sophisticated customer segmentation at the next level of the DMLM approach.

At the *third level*, any available customer data (see §3) is considered in a data-mining process based on a CHAID algorithm so as to determine the profit-maximizing microsegmentation of the customer base.

[1] From (7), it follows that $\lambda(s_3 - s_1) = n(c_3 - s_1)$. From (8), $\lambda < n$, hence the conclusion.

Therefore, microsegments with at least 500 names are formulated systematically to confirm whether the particular variable constellation of this microsegment reaches s^* or not. Then the following simple decision rule is applied:

$s_j = s^* \Leftrightarrow$ customers of microsegment j will be advertised regularly.
$s_j < s^* \Leftrightarrow$ with respect to the elasticity evaluated at Level 1, customers of microsegment j will either be dropped, advertised less often, or stimulated with a special reactivation series in order to reach s^*.

For customer microsegments j with $s_j < s^*$, the elasticities evaluated at DMLM Level 1 can be used to analyze whether a reduction of promotions will be sufficient to increase s_j at least to the required level s^*. We wish to emphasize that at DMLM's Level 3, we consider many small microsegments ($j \gg 3$) explicitly.

At Rhenania, we experienced that in some cases s_j could be raised by about 20% through reduced advertising. Especially for low-value customers who rarely receive mailings, a reduction in marketing activities has almost no effect. Greater profits were achieved through special reactivation packages. However, even combinations of both were insufficient to improve s_j by more than 30%. Therefore, in the case of Rhenania, as a rule of thumb, every customer microsegment with $s_j < s^*/1.3$ will be excluded from any future mailing activities.

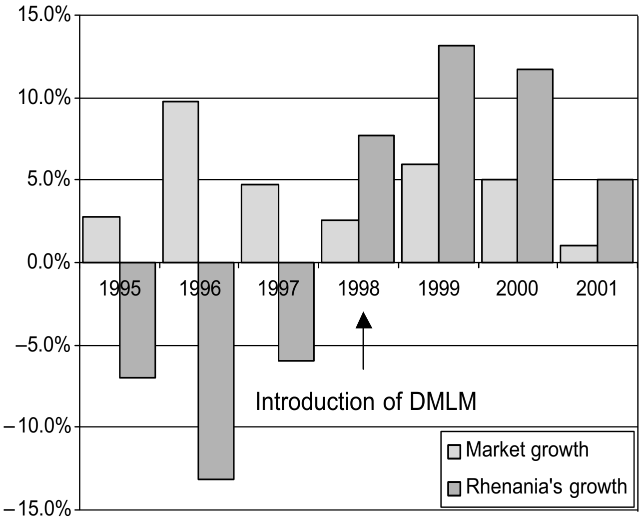
5. Turnaround at Rhenania Using DMLM

Commencing in May 1998, the implementation of DMLM led to enormous economic changes as can be seen in the following figures. Applying the model even helped "beat the market" (see Figure 3). From January 1998 to December 2001, the market grew by approximately 15%, while Rhenania was able to increase its sales by 43%.

Level 1 analysis revealed 25 catalogs per year to be the optimal number of campaigns for Rhenania. Furthermore, as a result of the Level 2 analysis, the mail volume almost doubled within the first 12 months of applying DMLM. Each customer within this annual mail volume was selected by the iterative data-mining process at Level 3. Here, in order to determine the profit-maximizing microsegmentation of the customer base (mainly to weed out one-time, inactive, and low-volume buyers from the customer base), any available customer data are considered so as to aggregate microsegments that reach the optimal threshold value s^*.

Compared with the numbers of the active customer base in 1996, sales and profit developed as shown in Figure 4.

Figure 3 **Results of Implementation of DMLM at Rhenania: Market Growth vs. Rhenania's Growth**



Note. While the overall market volume grew by an average of about 5% between 1995 and 2001, Rhenania was losing market share before it introduced DMLM in 1998. In each year since then, Rhenania has outperformed the market by a considerable margin.

The DMLM approach was so effective that Rhenania outperformed the market substantially and was able to acquire two major competitors (one of them larger than Rhenania itself). As a result, the Rhenania group improved its market position from number 5 to number 2.

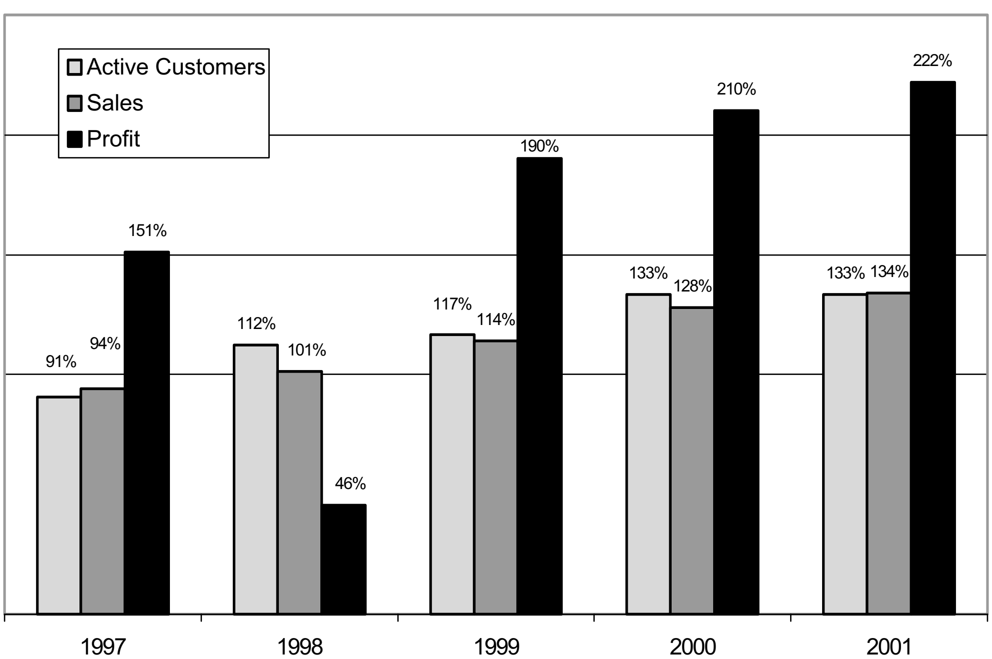
Before Akzente and Mail Order Kaiser were acquired by Rhenania, both companies lost money for five consecutive years. Using DMLM, however, their operational business became profitable within one year.

6. Dynamic Multidimensional Marketing (DMDM)

As already indicated, Rhenania acquired its competitors Akzente and Mail Order Kaiser in 2001. Subsequently, customer data for the three different companies, with their separate catalog brands, was merged and stored in one single database. Up to that point in time, there was a lack of experience on the part of Rhenania's management about how to control and optimize several direct marketing brands simultaneously. There was no global optimization model, because DMLM was designed for a single brand only. Furthermore, it was not even clear whether it is advantageous to maintain three brands or to combine them into one "super-catalog." However, the super-catalog was considered as a last resort in the event that the three-brand strategy failed.

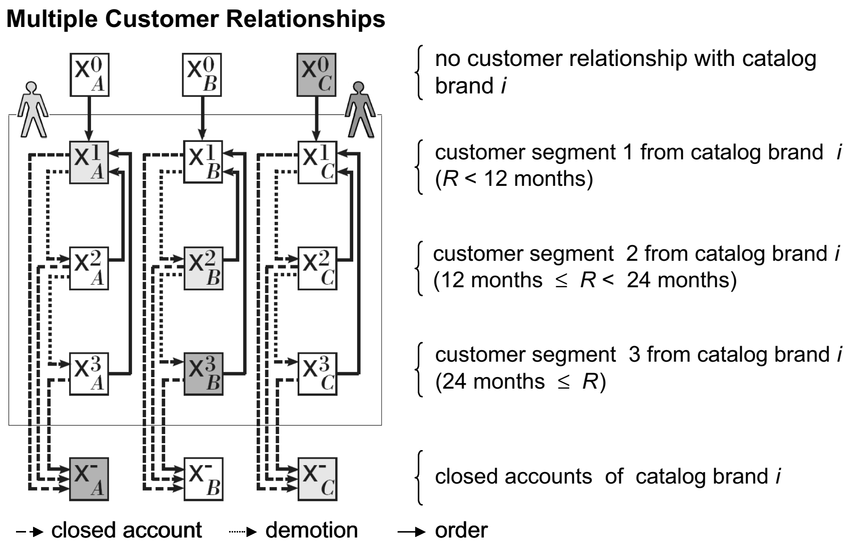
DMLM was applied to each company separately, which improved the profitability for all three within months. Within the time frame of one year, both acquisitions—Akzente and Mail Order Kaiser—were able to avoid losses and earn profits in their operational business for the first time in several years.

Figure 4 **Increase of Active Customer Base, Sales, and Profit as a Result of Using the DMLM Approach**



Note. After losing customers steadily between January 1997 and April 1998, Rhenania increased its active customer base, sales, and profit substantially by using the analytical approach of DMLM.

Figure 5 **Multiple-Customer Relationships in a Two-Customer Example**



Note. Since customers can potentially order from each of the three catalog brands, multiple-customer relationships are possible. Customers are segmented using the recency (*R* criteria) of the last purchase. The rate of transactions within or between brands depends on the brand-related response rates of each customer segment. For example, customer Light-Grey is assigned to Segment #1 for Brand *A*, Segment #2 for Brand *B*, and has a closed account for Brand *C*; customer Dark-Grey has a closed account for Brand *A*, is assigned to Segment #3 for Brand *B*, and is not a customer of Brand *C*.

Unfortunately, from Fall 2001, the mail-order industry was severely affected by the persisting economic downturn. In this difficult environment, we recognized that running the DMLM decision process for each brand separately was inadequate because cross-brand correlations and such interdependencies as cost effects and multiple-customer relationships had to be considered in an overall optimization process.

Figure 5 illustrates multiple-customer relationships in a two-customer example. Again, customers for each catalog brand are segmented according to the recency of their last purchase. The rate of transition within and across brands depends on the brand-related response rates of each customer segment.

Customer Light-Grey is currently assigned to Segment #1 for Brand *A*, Segment #2 for Brand *B*, and has a closed account for Brand *C*. Customer Dark-Grey has a closed account for Brand *A*, is assigned to Segment #3 for Brand *B*, and is not a customer of Brand *C* at all. It is evident that these customer relationships are multidimensional.

We were curious about the development of elasticities of single-brand customers who become multi-brand customers. Clients of Akzente, Mail Order Kaiser, and Rhenania were (usually) not aware that these catalog brands originated from a single company, namely, the Rhenania group. Our main concern was that the transition of single-brand to multibrand customers would exert a strong negative impact on the relationships because the number of catalogs received would increase.

Here we encountered a totally unexpected phenomenon. We learned that there were customers who reacted very negatively to receiving even one additional catalog per year for a particular brand but had no problem at all with receiving 25 additional catalogs for a different brand. Unfortunately, this was not true for all customers. Therefore, we established that several brand elasticities exist for a single customer: one for each brand and one global elasticity over all three brands.

In the following section we will highlight the main differences between the regular DMLM and the multicatalog-brand approach called DMDM.

In addition to the one-dimensional DMLM decision process, at DMDM Level 1, we used the global elasticity (as an upper bound on total mailings received by a single customer) to determine the optimal number of campaigns for each brand and each customer segment.

Secondly, at the Level 2 analysis of the modified DMLM approach, the customer segments to be included in the mailing for each brand are determined subject to an explicit consideration of economies of scale and scope. Consequently, different brand-specific threshold values s^* are determined. They are utilized further at DMDM Level 3.

Thirdly, at the Level 3 analysis, we see the major differences and gains in overall improvements of the DMDM model performance. It is important to recall that the main purpose of the Level 3 analysis is to separate customers who contribute to overall profits from those who do not.

For the DMDM approach, a distinction between brand-independent (e.g., personal, demographic, and geographic data) and brand-related (e.g., purchase, promotion, and contact history) variables is now possible and effective.

In addition, a powerful predictor beyond the brand-related variables is the so-called multiple-customer characteristic measured by the various combinations of customer catalog brand relationships. This measure can be understood as an indicator of mail-order affinity. For example, for three different catalog brands and the issue of whether a customer relationship exists or not, the number of possible combinations is $2^3 = 8$.

Finally, cross-brand correlations and interdependencies are integrated in this overall optimization process. All in all, the increased availability of customer information yielded a more complete profile of customers from Rhenania group's three brands. Thus, this allowed us to tailor the marketing efforts to individual customer preferences even more effectively. This capability has been labeled by some authors as "customer addressability" (e.g., by Blattberg and Deighton 1991 or Chen and Iyer 2002). Based on all these variables, the elasticities, and the threshold values, the following decisions are made:

- which customer receives regular promotions of which brand in what frequency
- which customer receives special offer promotions in order to reactivate or to increase the number of customer-brand relationships.

The entire DMDM process is highly customer focused. It does not maximize the profit of single campaigns or of single catalog brands but, rather, the profit of the customer base over all campaigns of all brands included in the optimization process.

7. Mathematical Details of DMDM

With the acquisition of two of Rhenania's competitors, customer data from three different companies, with separate catalog brands, were stored in a single database. We now show the changes in marketing strategy and analysis in a three-company (i.e., catalog brand) example. These companies or "brands" are labeled A, B, and C.

Considering more than one brand expands DMLM into a multidimensional analysis. For each of the brands in question, the three-stage DMLM analysis must be applied. Furthermore, the mutual correlations and interdependencies must be integrated in the overall optimization process.

The total number of catalogs a customer i receives over the planning horizon H, is, at most, equal to the sum over all different catalogs of all brands:

$$n_i = n_i^A + n_i^B + n_i^C \leq n_{\text{opt}}^A + n_{\text{opt}}^B + n_{\text{opt}}^C. \tag{10}$$

In the mail-order business, one can typically expect a negative nonelastic customer response to an increasing number of promotions. This means that the greater the total number of campaigns, the greater the probability of a more elastic negative impact on the average sales per customer and campaign s.

For this multidimensional approach called DMDM, the Level 1 analysis must now deal with the global elasticity over all brands. To clarify, let us assume that, optimally, single-brand customers should receive 25 mailings. As one can imagine, sending such customers 75 mailings for three catalog brands instead of 25 for one brand leads to lower average response rates and lower average order sizes per customer. For example, a customer who, on average, ordered books for €25 per mailing when s/he received 25 mailings, will possibly order for only €7 per mailing if s/he receives 75 mailings. Based on economic rationale and empirical observation, it is reasonable to assume that larger numbers of mailings lead to accumulated response rates and order sizes that increase at decreasing rates. Therefore, in the case of multiple-customer relationships, the global elasticity of a customer segment j with respect to the average sales per customer and campaign s has to be considered as:

$$\varepsilon_s(n_j) = \frac{\partial s/\partial n_j}{s/n_j} \leq \varepsilon_s(n_j^k) = \frac{\partial s/\partial n_j^k}{s/n_j^k} \qquad k = \{A, B, C\}. \tag{11}$$

Depending on the individual elasticities, in some cases customer value can be optimized by curtailing the aggregate number of mailings received over the planning horizon.

At the Level 2 analysis, the total mail volume, the total cost function subject to explicit consideration of economies of scale, and brand-specific threshold values s^* are determined.

Since customers can potentially order from each of the three catalog brands, multiple-customer relationships are possible. Consequently, one customer can receive mailings from more than one brand. Therefore, the available mail potential V_{MP}—the number of different customers or prospects in the database that can receive mailings—is, in strictly mathematical terms, less than the sum of the mail potential for each brand.

Because of these multiple-customer relationships, the total of prevailing mail volume V over the entire planning horizon H, is not limited by V_{MP} and is simply the sum of mail volume for all three brands. The following conditions hold:

$$\begin{aligned} V_{MP} &= V_{MP}^A \cup V_{MP}^B \cup V_{MP}^C < V_{MP}^A + V_{MP}^B + V_{MP}^C \\ &\Leftrightarrow V_{MP}^k \cap V_{MP}^l \neq \{\ \} \qquad k, l = \{A, B, C\}, \qquad (12) \\ V &= V^A + V^B + V^C. \qquad (13) \end{aligned}$$

When the mail volume is doubled or even tripled, production cost per mailing (layout, printing, shipping, etc.) will decrease substantially. Due to these economies of scale and synergies, we obtain the following cost function:

$$C(V) = C^A(V^A, V^B, V^C) + C^B(V^A, V^B, V^C) + C^C(V^A, V^B, V^C) \quad \text{with } \frac{\partial C^k}{\partial V^k} > 0, \ \frac{\partial^2 C^k}{\partial V^{k2}} \leq 0, \ \frac{\partial C^k}{\partial V^l} < 0 \Leftrightarrow k \neq l, \qquad k, l = \{A, B, C\}. \tag{14}$$

The larger the mail volume V, the larger the economies of scale and scope. The cost function of one brand is no longer independent of the mail volume of the other brands. The marginal costs of brand k decrease with an increasing mail volume of brand l.

Because of super saturation (e.g., by bothering the customers), we can also expect the rate of closed accounts x to rise with an increasing number of campaigns n:

$$\frac{\partial x}{\partial n} > 0 \qquad n\uparrow \implies x\uparrow. \tag{15}$$

Especially at Level 3 of the DMDM analysis, for each customer, a distinction between one-dimensional (brand-independent)[2] and multidimensional (brand-related)[3] variables is necessary. Each dimension of brand-related variables can be used as a predictor of customer behavior. In a data-mining process based on a CHAID algorithm, variable constellations are constructed systematically in order to determine the profit-maximizing microsegmentation of the customer base.

At Level 3 of the data-mining process, it was revealed and subsequently proven empirically, that brand-related customer preferences in product categories, as well as customer behavior measured in variables such as RFM, are very strong predictors of customer behavior in other brands.

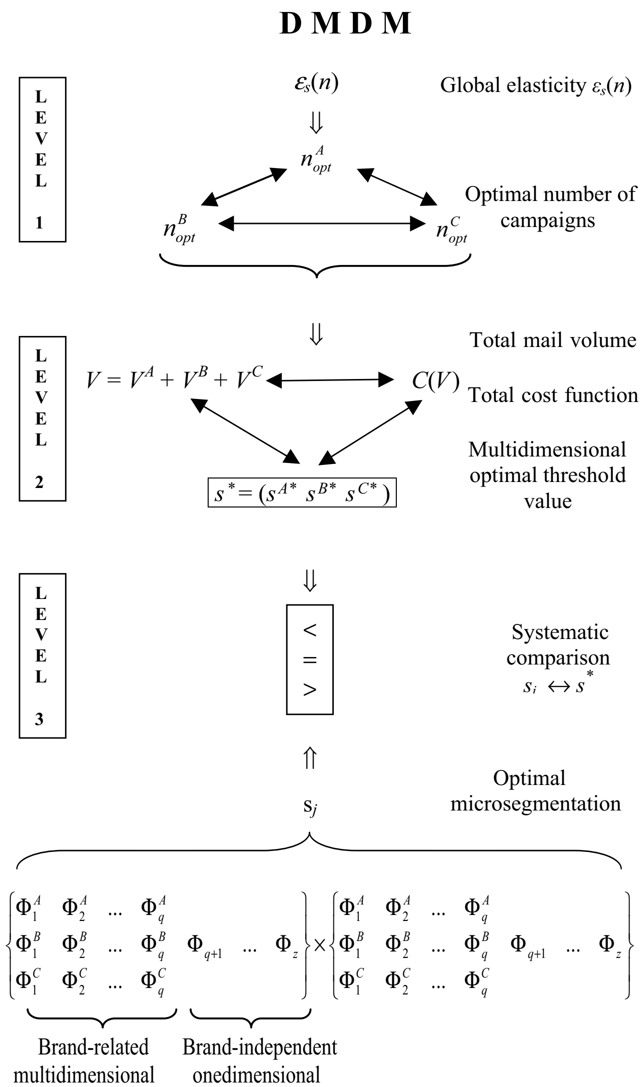
As already described in §6, the multiple-customer characteristic is a powerful additional predictor (beyond the brand-related variables) that can be understood as a mail-order affinity indicator. For m different brands, the number of possible combinations κ can be calculated easily.

The whole DMDM process is summarized in Figure 6.

Consequently, there are three main modes of separate catalog interaction. One is the cost; another is through the global cross-elasticity; and a third is by means of brand-related variables in the Level 3 CHAID analysis. In particular, as pointed out earlier, the mail-order affinity indicator is a powerful predictor for estimating the "true" value of a customer.

Finally, it can be stated that DMDM

Figure 6 **Summary of Entire DMDM Process**



Note. At Level 1, global elasticity $\varepsilon_s(n)$ and the optimal number of campaigns n_{opt} are evaluated. Determination of total mail volume V, costs $C(V)$, and the multidimensional optimal threshold value s^* follow at Level 2. A systematic comparison between combinations of z different variables Φ and s^* on Level 3 delivers the optimal microsegmentation of the customer base.

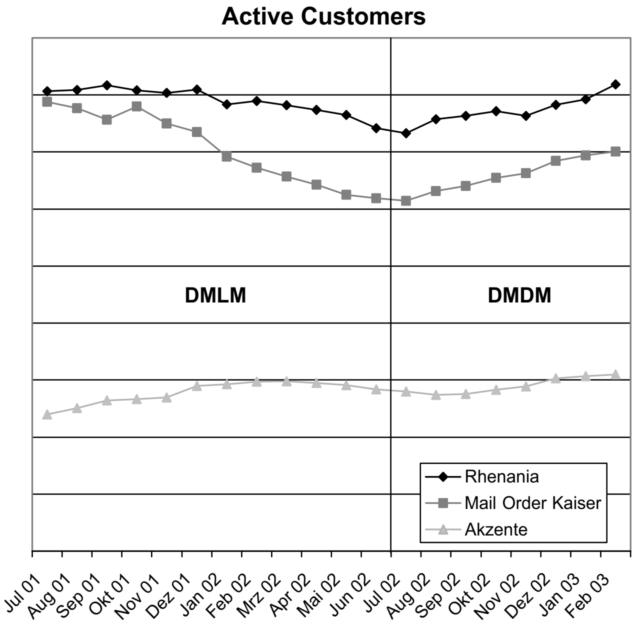
- considers mutual correlations and interdependencies,
- enables a more effective microsegmentation of the customer base,
- improves resource allocation, e.g., direct marketing expenses and reactivation efforts, and
- increases the number of multibrand relationships with higher revenue per customer and prolonged customer relationships.

Section 8 shows that by applying DMDM, Rhenania group's performance could be decoupled favorably from the overall market trend.

[2] For example, personal, demographic, and geographic data.

[3] For example, purchase, promotion, and contact history.

Figure 7 Development of Active Customers for Each Brand Since July 2001



Note. From July 2001 to July 2002, Rhenania applied three different DMLM processes separately to its catalog brands. Then, in an overall optimization, these processes were linked in a multidimensional approach with subsequently synchronized marketing communication called DMDM.

8. Total Customer View Using DMDM

After the acquisitions of Akzente and Mail Order Kaiser in 2001, Rhenania started to run the DMLM process separately for each catalog brand. Interdependencies had not been considered appropriately, and the overall optimum could not be achieved. DMLM, which was designed to optimize dynamically, mailing campaigns of a single catalog brand only, did not leverage multicatalog-brand effects such as utilization of prior-customer ordering behavior across the three catalog brands, optimization of customer value and customer share across those brands, and a consideration of economies of scale and scope. Moreover, commencing in Fall 2001, the mail-order industry was severely hit by a persistent economic downturn.

It took about one year of data collection and experience to develop the multidimensional approach called DMDM, i.e., to connect the three DMLM decision processes across catalog brands. DMDM's starting point was July 2002. The development of active customers for each brand since July 2001 is shown in Figure 7. This is the point in time at which the latest acquisition was made and the data for all catalog brands was stored in one database.

In the first row of Table 1, we show the degree to which products sold by Akzente, Mail Order Kaiser, and Rhenania overlapped before and after Akzente and Mail Order Kaiser were acquired. Since all competitors use a similar set of vendors, there was already some overlap before the acquisitions (6.4% and 4.3%). In order to improve the product portfolio of all three catalog brands, this overlap was increased substantially within two years of acquisition (34.1% and 9.3%). The overlap is much higher for Rhenania and Akzente, given that their customer bases are rather similar, while Mail Order Kaiser serves rather different clients. The numbers reported are based on the item overlap.

In the second row of Table 1, we consider any customer who ever ordered products from Akzente, Mail Order Kaiser, or Rhenania. Again, we observe that some clients ordered both from Rhenania and Akzente (4%) and Rhenania and Mail Order Kaiser (5.6%). These numbers represent the percentage of customers who were, or are, common to the house lists of Rhenania and Akzente or Mail Order Kaiser. As we can see, our new concept helped increase this overlap substantially to 6.7% for Rhenania and Akzente and to 10.6% for Rhenania and Mail Order Kaiser.

However, the most impressive results can be reported for the overlap of active customers across catalog brands. The last row in Table 1 reveals that only 2.4% and 7.7% of Rhenania's active customers were also customers of Akzente and Mail Order Kaiser. This overlap could be improved substantially to 16% for Rhenania and Akzente and to 26.1% for Rhenania and Mail Order Kaiser. Table 1 illustrates the degree to which synergies in merchandized products and multiple-customer relationships have developed since 2001.

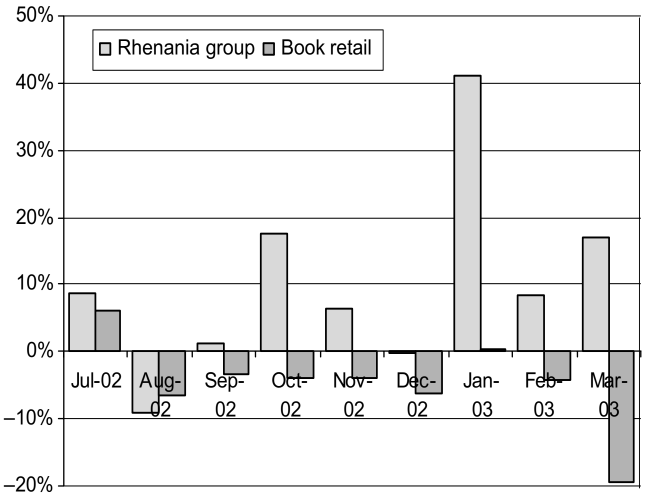
All in all, our new approach enabled a more effective microsegmentation of customers who

Table 1 Overlap of Active Customers Across Catalog Brands

	Rhenania and Akzente		Rhenania and Mail Order Kaiser	
	Before acquisition (%)	After acquisition (%)	Before acquisition (%)	After acquisition (%)
Products	6.4	34.1	4.3	9.3
All customers	4.0	6.7	5.6	10.6
Active customers	2.4	16.0	7.7	26.1

Note. Changes of overlap in products as well as all and active customers across catalog brands before and after each acquisition.

Figure 8 **Sales Growth at Rhenania Group and German Book Retailing (Current to Previous Year), Decoupled**



contributed positively to overall profitability across all brands and those customers who did not do so. The approach helped improve resource allocation, for instance, with respect to direct-mailing expenses and reactivation efforts. We were also able to target single- or two-brand customers by transforming those relationships into two- or three-brand relationships with higher revenue per customer. Customer relationships could be prolonged because of a lowering of the required revenue threshold value s^*, as a result of economies of scale and scope. Finally, microsegmentation of customers could be based on a richer set of brand-independent and brand-related variables. As a consequence, Rhenania group's performance was decoupled from the overall market trend (see Figure 8).

An important part of DMDM, which follows after the pure optimization model, is synchronized marketing communication. To emphasize the importance of this policy, we modified the name of this dynamic and multidimensional process from Dynamic Multidimensional *Modeling* into Dynamic Multidimensional *Marketing*. A highly standardized microsegment-related communication process (with a personal and individualized appeal that is perceived by customers as a one-to-one dialog) plays a crucial role in raising low-value microsegments beyond the threshold value s^*. Because of multiple-customer relationships, these direct marketing concepts must be different for each catalog brand in timing, dramaturgy, and creative approaches.

9. Summary

In this paper, we demonstrated that by applying our dynamic multilevel modeling (DMLM) approach, Rhenania was able to turn its mail-order business around and even beat the market. The DMLM approach was so effective that Rhenania could buy out two of its major competitors. However, as a consequence of these acquisitions, the Rhenania group faced new challenges. DMLM, which was designed to optimize mailing campaigns of a single catalog brand over a rolling horizon, was unable to leverage multicatalog-brand effects such as utilization of prior-customer ordering behavior across the three catalog brands, optimization of customer value and customer share across those brands, and consideration of economies of scale and scope. Therefore, DMLM had to be extended and modified.

Our enhanced dynamic multidimensional marketing (DMDM) approach is based on the observation that there are microsegments that respond differently to the global number of catalogs from Rhenania group's three brands and the number of catalogs for each separate brand. DMDM helped to provide greater insight into the specifics of multicatalog-brand customer relationships. For example, a more disaggregated (micro-) segmentation is based on a richer set of brand-dependent, i.e., multidimensional customer data about response rates, ordering, or return behavior. DMDM also takes multibrand relationships into consideration and helps to develop single- or two-brand customer relationships into two- or three-brand relationships. Given the fact that multibrand relationships affect revenue and cost functions, and as a consequence, the optimal mailing policies and resource allocations across microsegments, the hitherto separate DMLM decision processes were integrated and optimized simultaneously in DMDM. Last but not least, because a more complete view of the individual customer relationship was obtained, reactivation efforts could be improved. As a consequence, the Rhenania group's performance was decoupled from the overall market trend.

We believe that the major strength of DMDM lies in its ability to provide a more detailed understanding of multicatalog-brand customer relationships. As long as we had customer knowledge restricted to one catalog company only, we did not understand the specifics of multicatalog-brand relationships. The acquisition of two different companies enabled us to gain a more complete view of customer behavior and characteristics. After merging three customer databases and running a series of multibrand experiments, we could evaluate the economic value of customer relationships more accurately. Some customers who had previously been considered barely profitable were now evaluated as profitable because of their multibrand relationships. In other words, "the scales fell from our eyes."

During the ISMS Practice Prize competition at the 2003 Marketing Science Conference, the CEO of

Rhenania, Frederik Palm, stressed that the contribution of the DMDM model provided real value to the firm's customers, mainly through personalized communication. Since 1998, each customer address to which Rhenania mails is selected by applying DMLM. This new model helped to turn around not only Rhenania, but also its two acquisitions, Akzente and Mail Order Kaiser. Frederik Palm also emphasized that the enhanced DMDM approach was critical to the success of Rhenania group during the difficult and turbulent times after late 2001. Rhenania group has outperformed its industry in 2002 and 2003. Rhenania group's CEO attributed this success exclusively to DMDM.

Given that many industries are characterized by multibrand issues that are similar to those addressed in DMDM, we are confident that modified versions of our approach can be used to solve dynamic, multibrand issues in industries such as financial services, telecommunications, etc. We have already received requests from different companies in these industries. This seems to confirm the relevance of our approach to different firms and industries.

Nonetheless, we see a continuing need for future research. On the one hand, we only applied DMDM to three catalog brands of Rhenania group. It would be helpful to apply our new approach to other companies and industries in order to gain greater insight into the generalizability of DMDM. On the other hand, there is still room for improvement to the DMDM modeling process. Currently, this approach follows a hierarchical structure and does not, for example, explicitly model a functional relationship between the optimal number of campaigns at Level 1 and the decisions made at Levels 2 and 3. However, by repeatedly applying the three-level approach to Rhenania group's customers, we are confident that our approach is very close to achieving the overall optimum. We also see potential for improving our model by taking into account catalog composition (color, graphics, content). In particular, allowing for microsegment-specific catalogs adds complexity but also potentially higher profits. However, such a micromarketing approach has to be balanced against the advantages of larger catalog lot sizes (economies of scale).

We look forward to more contributions to the somewhat neglected but important field of modeling and optimization in direct marketing.

Acknowledgments

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Appendix

PROOF.

$$\begin{aligned} c_3 &= s_1(n-\lambda)/n + s_3\lambda/n \\ &= s_1(n-\lambda)/n + s_3 - s_3(n-\lambda)/n \\ &= s_3 + (n-\lambda)/n(s_1 - s_3), \end{aligned}$$

$$s_1 > s_3 \Rightarrow (n-\lambda)/n(s_1-s_3) > 0 \Rightarrow s_3 < c_3. \quad \square \qquad \text{Q.E.D.}$$

Notation

- a average order size
- C cumulative cost function over n mailing campaigns
- c_j variable costs per customer of mailing to segment(s) $[1, j]$
- c_j fixed costs per customer of mailing to segment(s) $[1, j]$
- d_j demoted customers of segment j, moving to the next segment: $d_j = (1-r_j)^{n_{\mathrm{opt}}} v_{j1}/n_{\mathrm{opt}}$; $j = \{1, 2\}$
- g_n number of gained new customers in campaign n: $g := g_1 = g_2 = \cdots = g_{n_{\mathrm{opt}}}$
- H planning horizon, i.e., $H = [1, n_{\mathrm{opt}}]$
- j index of segments
- k index of catalog brands
- κ mail order affinity indicator
- L set of limitations, such as budget constraint, supply structure, production time, minimum required distance between two campaigns, etc.
- n number of direct marketing campaigns ($n \le n_{\mathrm{opt}}$)
- $n_{\max}$ maximum number of feasible direct marketing campaigns
- n_{opt} profit-maximizing number of direct marketing campaigns
- P cumulative profit function over n mailing campaigns
- r response rate
- S cumulative sales function over n mailing campaigns
- s_j average sales per customer of segment j: $s_j = r_j \cdot a_j$
- s^{k_*} minimum required sales per customer per segment per campaign for catalog brand k
- t timing, appropriate mail dates
- v mail volume, number of names
- v_{jn} mail volume, number of names in segment j to the time of campaign n
- V volume, number of names contacted over the whole planning horizon: $V_{jn} = \sum_{i=1}^{n} v_{jn}$; $j = [1, 3]$
- V_{MP} available mail potential
- x_{jn} number of deleted customers from segment j leaving the house list after campaign n: $x_n := x_{j1} = x_{j2} = \cdots = x_{jn_{\mathrm{opt}}}$
- Φ predictor variables
- $\varepsilon_a(n)$ elasticity of average order size of customer segments regarding additional promotions

$\varepsilon_r(n)$ elasticity of response rate of customer segments regarding additional promotions

$\varepsilon_s(n_j)$ global elasticity of a customer segment j regarding s.

References

Berger, P. D., N. I. Nasr. 1998. Customer lifetime value: Marketing models and applications. *J. Interactive Marketing* **12**(1) 17–30.

Biggs, D., B. de Ville, E. Sun. 1991. A method of choosing multiway partitions for classification and decision trees. *J. Appl. Statist.* **18**(1) 49–62.

Bitran, G., S. Mondschein. 1996. Mailing decisions in the catalog sales industry. *Management Sci.* **42**(9) 1364–1381.

Bitran, G., S. Mondschein. 1997. A comparative analysis of decision making procedures in the catalogue sales industry. *Eur. Management J.* **15**(2) 105–116.

Blattberg, R., J. Deighton. 1991. Interactive marketing: Exploiting the age of addressability. *Sloan Management Rev.* **33**(Fall) 5–14.

Blattberg, R., J. Deighton. 1996. Manage marketing by the customer equity test. *Harvard Bus. Rev.* **74**(4) 136–144.

Bult, J. R. 1993. Semiparametric versus parametric classification models: An application to direct marketing. *Marketing Sci.* **12** 330–390.

Bult, J. R., T. Wansbeek. 1995. Optimal selection for direct mail. *Marketing Sci.* **14**(4) 378–394.

Campbell, D., R. Erdahl, D. Johnson, E. Bibelnieks, M. Haydock, M. Bullock, H. Crowder. 2001. Optimizing customer mail streams at Fingerhut. *Interfaces* **32**(1) 77–90.

Chen, Y., G. Iyer. 2002. Research note: Consumer addressability and customized pricing. *Marketing Sci.* **21** 197–208.

Colombo, R., W. Jiang. 1999. A stochastic RFM model. *J. Interactive Marketing* **13**(3) 2–12.

Dwyer, F. R. 1989. Customer lifetime valuation to support marketing decision making. *J. Marketing* **3**(4) 8–15.

Elsner, R. 2003. *Optimiertes Direkt- und Database-Marketing unter Einsatz mehrstufiger dynamischer Modelle* (*Optimized Direct and Database Marketing Using Multilevel Dynamic Models*). Deutscher Universitäts-Verlag, Wiesbaden, Germany.

Elsner, R., M. Krafft, A. Huchzermeier. 2003. Optimizing Rhenania's mail order business through multi-level modeling. *Interfaces* **33**(1) 50–66.

Hansotia, B. J., P. Wang. 1997. Analytical challenges in customer acquisition. *J. Direct Marketing* **11**(2) 7–19.

Haughton, D., S. Oulabi. 1993. Direct marketing modeling with CART and CHAID. *J. Direct Marketing* **7**(3) 16–26.

Hosmer, D. W., S. Lemeshow. 2000. *Applied Logistic Regression*, 2nd ed. John Wiley & Sons, New York.

Kestnbaum, R. D., K. T. Kestnbaum, P. W. Ames. 1998. Building a longitudinal contact strategy. *J. Interactive Marketing* **12**(1) 56–62.

Malthouse, E. 1999. Ridge regression and direct marketing scoring models. *J. Interactive Marketing* **13**(4) 10–23.

Malthouse, E. 2001. Assessing the performance of direct marketing scoring models. *J. Interactive Marketing* **15**(1) 49–62.

Malthouse, E. 2003. Scoring models. D. Iacobucci, B. Calder, eds. *Kellogg on Integrated Marketing*, John Wiley & Sons, Nw York, 227–249.

Pfeifer, P., R. Carraway. 2000. Modeling customer relationships as Markov chains. *J. Interactive Marketing* **14**(2) 43–55.

Reinartz, W. J., V. Kumar. 2003. The impact of customer relationship characteristics on profitable lifetime duration. *J. Marketing* **67**(January) 77–99.

Wunderman, Lester. 1997. *Being Direct.* Random House, New York.

Zahavi, J., N. Levin. 1995. Issues and problems in applying neural computing to target marketing. *J. Direct Marketing* **9**(3) 33–45.

Zahavi, J., N. Levin. 1997. Applying neural computing to target marketing. *J. Direct Marketing* **11**(1) 5–22.