Optimal product line designing: A comparison of different discrete choice-based approaches

Friederike Paetz
Clausthal University of Technology
Winfried Steiner
Clausthal University of Technology
Harald Hruschka
University of Regensburg

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Optimal product line designing:
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Nowadays, short product life cylcles force companies to frequently develop and offer new products. In order to gain revenues and stay competitive, companies have to carefully design their revenue-maximizing product lines. Often, individual consumer preferences derived from discrete choice experiments build the input for product line optimization. Basically, two different approaches, e.g., a simultaneous approach and a separate approach exist, that differ in their consideration of consumers' preference heterogeneity. We compared these two types of product line design approaches w.r.t. to their performance to detect revenue-maximizing product lines. We use a Monte Carlo simulation study and found the simultaneous approach to outperform the separate approach and therefore being more robust to biases in the recovery of preference structures, e.g., part-worth utility estimation. Furthermore, we detect several experimental factors that determine the approaches' performances.

Keywords:
Product line design, Discrete Choice Experiments, Preference heterogeneity

Track:
Innovation Management & New Product Development

1 Introduction and Objectives

Due to the increasing competition in consumer markets, companies have to frequently develop new products and sell them in order to gain revenues and stay competitive. In this context, the question arises, which product variations should be offered? Hence, which product variants are most promising? These questions are bundled in so called product portfolio decisions.
On the one hand, if a company decides to sell one single product to the whole market, it implicitly assumes homogeneous preferences of consumers. Hence, one single product tries to target all consumers within the relevant market and, therefore, has to balance potential heterogeneous needs (Fruchter & Fligler, 2007). Based on the company's objective, it may sell a single product which maximizes its revenue, market share etc. On the other hand, if a company is aware of a very heterogeneous market, i.e., very different consumer preferences for certain product attributes, it might want to sell several product variants simultaneously. This results in so called product line decisions, that explicitly take into account preference heterogeneity.
The determination of single best products is commonly based on consumers' preferences and constitutes a challenging task (Balakrishan & Jacob, 1996). Often, the results of discrete choice experiments (DCEs) build the input for optimal product simulations and help to design the most promising, e.g., most preferred or most profitable, product.
Optimal product lines are often designed on the preference results from DCEs by using simulation software tools, too. However, in contrast to single product decisions, the effort for product line decisions increases. Beside the determination on the number of products within a certain product line, the company has to decide on the realization of different product variants (Tsafarakis, 2016, p. 619). In addition, cannibalization effects between product line's products have to be taken into account. In addition, if, for example, the maximization of revenues is the company's objective, the company has to consider scale effects in the production costs of different product variants etc.
Nowadays, the conjoint-analytic approaches, like DCEs, to determine consumer preferences as an input for optimal product line design are highly prominent (e.g. Tsafarakis, 2016). If we consider conjoint-analytic approaches and assume discrete product attributes, the optimal product line design problem constitutes a combinatorial problem, that is known to be NP-hard (Kohli & Krishnamurti, 1989). If the number of attribute levels or the number of products within a product line increases, the combinatorial problem increases exponentially (Steiner & Hruschka, 2003). Hence, the search for optimal product lines via complete enumeration is challenging, if not impossible. Therefore, optimization heuristics are frequently applied (e.g., Tsafarakis, 2016).

Independent of the considered optimization heuristic, two different types of approaches to design optimal product lines based on consumer preferences are thinkable: On the one hand, a so called *simultaneous approach* may be used. The simultaneous approach uses the individual preferences of all (interviewed) consumers as an input for product line optimization. Hence, it determines the optimal product line over the entire market. This approach therefore accommodates cannibalization effects between different product variants in a certain product line. However, it is computationally challenging. On the other hand, a so called *separate approach* could be performed. Basically, this approach relies on individual preference data as well, but consists of three subsequent steps. Within the first step, cluster analytic approaches, e.g., k-means clustering, are applied to cluster the individual preferences to segment-specific preferences. Within the second step, one single best product is determined for each segment. Subsequently, i.e., third step, the resulting single best products are then combined to an optimal product line. This approach is common practice in real marketing applications and alleviates the determination of the length of the product line. The number of product variants in a product line equals the number of disjunctive segments (compare the first step of the separate approach) at a maximum. For example, if two of four distinct segments yield the same single best product, then the optimal product line consists of three (= 4-1) different product variants. Since the optimization problem in the separate approach degenerates to the optimization of segment-specific single best products, the computation is much easier in comparison to the optimal product line design via the simultaneous approach. However, no cannibalization effects between different product variants are taken into account in the separate approach.

Obviously, the recovery performance of preference parameters (from DCEs) determines the final product line design as well as the resulting revenues of both different types of product line optimization approaches. Companies should therefore be interested in the robustness of different approaches for optimal product line design. This holds, because every divergence, e.g., under- or overestimation of product lines' revenues is undesirable if a company uses the results of a product line optimization tool for decision support. The central research question of this contribution could therefore be summarized as: Which product line optimization approach, e.g., simultaneous or separate approach, yields a better recovery of associated revenues? And is, therefore, more robust to biases in the recovery of preference parameters. In addition, further questions arise: First, which factors determine the recovery performance of the product line optimization approaches w.r.t. revenues? Second, which factors determine the recovery of preference parameters? Obviously, these factors are expected to actually coincide.

The remainder of this contribution is as follows: In section 2, we lay the theoretical foundation for our study and provide a brief review on relevant literature findings. In section 3, we report the results of a Monte Carlo simulation study w.r.t. approaches' differences between the real and the re-estimated revenues of product lines. Conclusions, managerial implications as well as limitations of our study and issues for future research are given in section 4.

2 Theoretical Foundations

In the following, we briefly review the Hierarchical Bayesian Multinomial Logit model in 2.1. Subsequently, we provide a brief introduction to the Genetic Algorithm in 2.2 and give a concise literature review on studies that compares the Genetic Algorithms to other heuristics in the field of product line design based on preference results from DCE in 2.3.

2.1 Hierarchical Bayes Multinomial Logit model

In the field of discrete choice analysis the Multinomial Logit (MNL) model is most popular to determine consumer preferences. Here, we follow random utility theory and assume a Gumble distributed error term ε. In the following, we are interested in individual preferences and therefore consider the utilities on an individual level: $U_{jm} = V_{jm} + \varepsilon_{jm}$, where $j = 1,\dots,J$ denotes the individual and $m = 1,\dots,M$ is an alternative. The deterministic part V_{jm} could be further described as $V_{jm} = \sum_{l=1}^{L} \sum_{k=1}^{K_l} x_{mlk} \cdot \beta_{jlk}$, where x_{mlk} is a design vector containing the dummy coding of level $k = 1,\dots,K_l$ of attribute $l = 1,\dots,L$ of alternative m and β_{jlk} is the individual part-wort utility parameter. The estimation of the individual part-worth parameters is our core purpose. Therefore, we rely on the Hierarchical Bayes (HB-) MNL model. Here, the choice probability $P_j(m)$ of each individual follows the MNL model

$$P_j(m) = \frac{\exp(\mu \cdot x_{mlk} \cdot \beta_{jlk})}{\sum_{r=1}^{R} \exp(\mu \cdot x_{rlk} \cdot \beta_{jlk})} \;\; (\mu > 0).$$

This constitutes the lower level of the hierarchical model. The upper level is the population level. In order to link the consumers' individual preferences to the population level, the multivariate Gaussian distribution is used as the probability distribution: $\beta_j \sim MVN(\overline{\beta}, \Sigma_\beta)$, where $\overline{\beta}$ denotes the vector of means of the distribution of individual part-worth utilities and Σ_β is the covariance matrix, which is assumed to be inverse Wishart distributed (Hein, Kurz, and Steiner, 2020, p. 30). In order to estimate $\overline{\beta}$, and Σ_β as parameters of the prior distribution commonly Gibbs Sampling methods are used. The conditional posteriori distribution of β_j is then obtained by a Metropolis-Hastings algorithm (Rossi, Allenby and McCulloch, 2005).

In order to measure the parameter recovery (in a simulation study, where the real individual part-worth utilities are known), we could simply rely on the correlation between the real and estimated individual part-worth utilities. However, several other measures to calculate parameter recovery exist, e.g., Root-Mean-Squared-Error (Paetz, Hein, Kurz and Steiner 2019, p. 8).

2.2 Genetic Algorithm

Holland (1975) was the first, who introduced the concept of the Genetic Algorithm. "The basis for this algorithm was the observation that a combination of sexual reproduction and natural selection allows nature to develop living species that are highly adapted to their environment." (Balakrishnan & Jacob, 1996, p. 1108). The Genetic Algorithm operates in an iterative manner and uses three genetic operators to generate candidate strings: Reproduction, also called selection, crossover and mutation.

To strengthen understandability, we are going to illustrate this for the optimization of single products. However, the trespass to product lines is straight forward (e.g., Steiner & Hruschka, 2003).

Selection: We consider an initial population, e.g., an initial pool of N product profiles. The population is either randomly generated or created based on heuristics. First, the fitness is determined by the value of the associated objective function (here: associated revenue of the product). Second, if a stopping condition is satisfied, e.g., the fitness does not significantly increase in comparison to the preceding iterations, the Genetic Algorithm stops. A concrete stopping rule might be, that the mean fitness value of the three best strings from the last three generations is less than X% worse than the fitness value of the three best strings in the current generation (Steiner & Hruschka, 2002, p. 586). In the reproduction/selection stage, we select a subset of N/2 product profiles based on their fitness.

Crossover: Here, randomly picked pairs of strings from the set of reproduced strings exchange genetic material to produce offsprings. For example, one-point cross over is conducted. Here, two product profiles are cut at one point each and exchange the material with is on the right hand side of the intersection. This results in two new offsprings.

Mutation: Among the offsprings, each product profile is provided by a certain chance to mutate. Hence, a product profile that realizes the third level of the second attribute may mutate, so that it realizes the first level of the second attribute after the mutation.

Once mutation is done, the new generated strings are evaluated and the next iteration starts.

2.3 Literature Review

The application of optimization heuristics like Genetic Algorithms, simulated annealing, beam search etc. is nowadays state-of-the-art in optimal product line design (Tsafarakis, 2016).[1]

All these optimization heuristics are known to provide near optimal solutions resp. are able to find (locally) optimal solutions. In several academic comparisons between different optimal product line heuristics, the genetic algorithm turned out as one of the most efficient search methods: Balakrishnan, Gupta and Jacob (2004) found the Genetic Algorithm to significantly outperform beam search in terms of the objective 'market share maximization', which is

[1]Obviously, these heuristics are used for optimal single product designs as well, if complete enumeration would last too long to find an optimal solution (Balakrishnan & Jacob, 1996).

somehow nested within revenue maximization. Hauser (2011) claimed that simulated annealing methods and Genetic Algorithms are the best near-optimal methods for product line designs in terms of computation time. Luo (2011) challenged inter alia Genetic Algorithm and simulated annealing methods within a simulation study and found comparable results of both methods. However, the Genetic Algorithm was found to converge quicker.
Based on the proven dominance of the Genetic Algorithm for product line optimization, we decided to use the Genetic Algorithm as the search method as well for our Monte Carlo simulation study.

3 Monte Carlo Simulation Study

In the following, we are going to describe the data generation process including the Monte Carlo simulation setup in 3.1. Then, we provide the discussion of the Monte Carlo study's results w.r.t. the comparison of the simultaneous and separate product line optimization approach in 3.2.

3.1 Data generation

We simulated individual data for 312 artificial respondents, e.g., we generated individual part-worth utilities and individual choices. The data generation process closely follows the procedure of Andrews, Ainsle, and Currim (2002) and Andrews and Currim (2003). We determined individual choices for 16 choice sets with three "real" alternatives and a no purchase option. Each alternative was described by five attributes with four levels, respectively. Since we are interested in revenue-maximizing product lines, we defined the first attribute as a price attribute with levels 90, 110, 130 and 150 monetary units. Here, we ensured a decreasing order of part-worth utilities for increasing prices and therefore viewed price in its function of transactional costs (and not as a quality signal resp. we considered no price reversals).
We further considered variable costs (and assume fixed costs not to depend on the product design here). The variable costs were built by taking into account the maximal price of 150 and the number of non-price attributes, e.g., four attributes. We built cost-ranges for (whole) products. The lower bound is calculated via $0.3 \cdot 150 = 45$ and the upper bound via $0.85 \cdot 150 = 127.5$. Hence, the costs of a product lie within $[45, 127.5]$. Without loss of generality, we considered the same cost levels for each of the four (non-price) attributes. We then draw four cost values for each attribute level from a uniform distribution over $[\frac{1}{4} \cdot 45, \frac{1}{4} \cdot 127.5]$ and rounded the values to integers .
The Monte Carlo simulation was based on six experimental factors that are well established in simulation studies in the context of preference heterogeneity (e.g., Andrews & Currim, 2003). We considered the number of segments (2, 3, 4), the separation between segments (small, large), the ratio of segments shares (symmetric, asymmetric), the inner-segment heterogeneity

(small, large), the no purchase share (low, high), and the variation coefficient of disturbances (low, high). We considered three replications. The optimization was performed by the Advanced Simulation Module (ASM) in Sawtooth Software using the Genetic Algorithm as the focal search method.

3.2 Data analysis

First of all, we were interested in the recovery of revenues by the two different optimization approaches. Recall that both an underestimation as well as an overestimation is undesirable. Therefore, we calculated the absolute difference between the real and estimated revenues and used this as the dependent variable. The independent variable was the type of optimization approach, i.e., simultaneous versus separate optimization approach. To identify significant differences we conducted t-tests. Table 1 displays the results.

	Absolute differences in revenues		t-values
	simultaneous	**separate**	(p-values)
mean abs. diff.	1976.2	3106.8	$t = 53.267$ ($p = 0.000$)
# segments			
2	2513.046	3360.790	$t = 15.400$ ($p = 0.000$)
3	1899.799	3135.465	$t = 39.148$ ($p = 0.000$)
4	1515.782	2824.224	$t = 54.379$ ($p = 0.000$)
separation			
0.5	2105.715	3746.844	$t = 100.244$ ($p = 0.000$)
2	1846.703	2466.809	$t = 17.407$ ($p = 0.000$)
Asym. shares			
0	1852.744	2953.551	$t = 47.716$ ($p = 0.000$)
1	2099.674	3260.102	$t = 46.460$ ($p = 0.000$)
inner-seg. het.			
0.05	2163.970	3486.965	$t = 50.712$ ($p = 0.000$)
0.25	1788.448	2726.688	$t = 49.199$ ($p = 0.000$)
no purch. likeli.			
0.07	2047.008	3150.522	$t = 43.639$ ($p = 0.000$)
0.15	1905.410	3063.131	$t = 49.790$ ($p = 0.000$)
variation coeff.			
0.1	1914.478	3029.799	$t = 41.276$ ($p = 0.000$)
0.3	2037.939	3183.854	$t = 53.276$ ($p = 0.000$)

Table 1: Absolute differences between real and estimated revenues by type of approach

Obviously, absolute differences between real and estimated revenues are significantly smaller for the simultaneous approach. This holds overall as well as for all cases.

Furthermore, we were interested in the impact of the experimental factors on the recovery of revenues, i.e., the absolute difference between the real and the estimated revenues. Therefore, we conducted one-way ANOVAs and t-tests. Here, the experimental factor was the independent variable and the absolute difference between the real and the estimated revenues constituted the dependent variable, respectively. Table 2 contains the results for the simultaneous approach on the left hand side and the results for the separate approach on the right hand side. Obviously, four factors significantly impact the recovery of revenues in both types of approaches. An increasing number of segments, a large separation, symmetric segment shares and a large inner-segment heterogeneity contribute to a significantly better recovery of revenues.

	Abs. diff. in revenues **simultaneous**	F-/t-values (p-values)
mean abs. diff.	1976.209	
# segments		$F = 16.919$ $(p = 0.000)$
2	2513.046	(2,3): $t = 3.410$ $(p = 0.001)$
3	1899.799	(2,4): $t = 5.832$ $(p = 0.000)$
4	1515.782	(3,4): $t = 2.289$ $(p = 0.023)$
separation		
0.5	2105.715	$t = 3.050$ $(p = 0.082)$
2	1846.703	
Asym. shares		
0	1852.744	$t = 2.770$ $(p = 0.097)$
1	2099.674	
inner-seg. het.		
0.05	2163.970	$t = 6.488$ $(p = 0.011)$
0.25	1788.448	
no purch. likeli.		
0.07	2047.008	$t = 0.905$ $(p = 0.342)$
0.15	1905.410	
variation coeff.		
0.1	1914.478	$t = 0.687$ $(p = 0.687)$
0.3	2037.939	

Significant factors in **bold** ($p < 0.1$).

	Abs. diff. in revenues **separate**	F-/t-values (p-values)
mean abs. diff.	3106.827	
# segments		$F = 3.013$ $(p = 0.051)$
2	3360.790	(2,3): $t = 0.976$ $(p = 0.330)$
3	3135.465	(2,4): $t = 2.426$ $(p = 0.016)$
4	2824.224	(3,4): $t = 1.512$ $(p = 0.132)$
separation		
0.5	3746.844	$t = 60.765$ $(p = 0.000)$
2	2466.809	
Asym. shares		
0	2953.551	$t = 2.904$ $(p = 0.089)$
1	3260.102	
inner-seg. het.		
0.05	3486.965	$t = 18.845$ $(p = 0.000)$
0.25	2726.688	
no purch. likeli.		
0.07	3150.522	$t = 0.234$ $(p = 0.629)$
0.15	3063.131	
variation coeff.		
0.1	3029.799	$t = 0.728$ $(p = 0.394)$
0.3	3183.854	

Significant factors in **bold** ($p < 0.1$).

Table 2: Impacts of factors on absolute difference between real and estimated revenues

It is expectable, that the factors' impacts on revenue's recovery may be traced back to factors' impacts on preference recovery. This is likely, because the individual preferences build the input for the product line optimization approaches. To check this, we calculated the correlation between the real and the estimated part-worth utility estimates and conducted one-way ANOVAs and t-tests. Table 3 yields the results:

	Correlation and F-/t-values (p-values)
mean correlation	0.917
# segments	$F = 0.005$ $(p = 0.995)$
2	0.921
3	0.919
4	0.908
separation	$t = 28.217$ $(p = 0.000)$
0.5	0.905
2	0.929
Asym. shares	$t = 8.048$ $(p = 0.005)$
0	0.924
1	0.910
inner-seg. het.	$t = 183.321$ $(p = 0.000)$
0.05	0.942
0.25	0.892
no purch. likeli.	$t = 4.062$ $(p = 0.045)$
0.07	0.912
0.15	0.922
variation coeff.	$t = 0.069$ $(p = 0.793)$
0.1	0.918
0.3	0.917

Factor levels yielding a significant better parameter recovery in bold ($p < 0.1$).

Table 3: Factor's impacts on part-worth utility parameter recovery

Obviously, our assumption holds for the factor separation and asymmetry of segment shares. Here, a larger separation and symmetric segment shares yield a better parameter recovery measured by the correlation between the real and estimated part-worth utilities. However, the number of segments does not significantly affect parameter recovery and for inner-segment heterogeneity we got a reverse result. Here, a smaller inner-segment heterogeneity leads to better parameter recovery, which contradicts our findings in Table 2. However, the correlations are quite high (> 0.89) for all cases and overall. Hence, we may infer, that the quality of parameter recovery cannot be seen as a driver for the recovery of revenues in our study.

4 Conclusions

Due to the increasing competition in consumer markets, companies have to frequently develop new products and sell them. In order to gain revenues and stay competitive they have to carefully design their revenue-maximizing product lines. Nowadays, individual consumer preferences derived from discrete choice experiments build the input for product line optimization. Basically, two different approaches, e.g., a simultaneous approach and a separate approach, exist, that differ in their consideration of consumers' preference heterogeneity. In our study, we relied on the Genetic Algorithm as product line optimization method for both approaches. We compared the robustness of these two types of product line design approaches by performing a Monte Carlo simulation study. The robustness was measured by the absolute difference in product lines' revenues based on the real and estimated preference parameters. We found the simultaneous approach to outperform the separate approach and therefore being more robust to biases in the recovery of preference structures.

We could further infer managerial implications: If the maximization of revenues is the company's objective, marketing managers should predominantly rely on the simultaneous product design optimization approach to ensure a good recovery of revenues. This optimization approach optimizes product lines over the entire market and accommodates cannibalization effects. Although, it is computational challenging, standard commercial software like the Advanced Simulation Modul of Sawtooth Software exist and could be easily applied.

Like every simulation study, our study inhibits some limitations: Obviously, we considered only three replications within the Monte Carlo study and did not incorporate fixed costs in the optimization. In addition, we used only one optimization method, e.g., the Genetic Algorithm and did not compare the results for varying optimization methods like grid search, beam search, or simulated annealing. However, since the Genetic Algorithm turned out as one of the dominant methods both in academical comparisons and in practical applications, our results provide a good benchmark for practical decision support. Within our simulation study, we regarded six experimental factors. However, further experimental factors, that more closely contribute to the increase of the search/solution space for the Genetic Alforithm, like the number of product attributes, would be interesting. We leave this for future research.

References

Andrews, R.L., Ansari, A., & Currim, I.S. (2002). Hierarchical bayes versus finite mixture conjoint analysis models: a comparison of fit, prediction, and partworth recovery. *Journal of Marketing Research*, 39, 87-98.

Andrews, R.L., & Currim, I.S. (2003) A comparison of segment retention criteria for finite mixture logit models. *Journal of Marketing Research*, 40, 235-243.

Balakrishnan, P., Gupta, R., & Jacob, V. (2004) Development of hybrid genetic algorithms for product line designs. *IEEE Transactions on Systems, Man, and Cybernetics*, 34, 468-483.

Balakrishnan P.V., & Jacob, V.S. (1996) Genetic algorithms for product design. *Management Science*, 42, 1105-1117.

Fruchter, G.E., & Fligler, A. (2007) The various brands in the optimal product line vs. the optimal single product. *Innovative Marketing*, 3, 15-22.

Hauser, J. (2011) Comment: new developments in product-line optimization. *International Journal of Research in Marketing*, 28, 26-27.

Hein, M., Kurz, P., & Steiner, W. (2020) Analyzing the capabilities of the HB logit model for choice-based conjoint analysis: a simulation study. *Journal of Business Economics*, 90, 1-36.

Holland, J. (1975) *Adaptation in Natural and Artificial Systems*. Ann Arbor: University of Michigan Press.

Kohli, R., & Krishnamurti, R. (1989) Optimal product design conjoint analysis: computational complexity and algorithms. *European Journal of Operational Research*, 40, 186-195.

Luo, L. (2011) Product line design for consumer durables: an integrated marketing and engineering approach. *Journal of Marketing Research*, 68, 128-139.

Paetz, F., Hein, M., Kurz, P., & Steiner, W. (2019) Latent class conjoint choice models: a guide for model selection, estimation, validation, and interpretation of results. *Marketing ZFP - Journal of Research and Management*, 41, 3-20.

Rossi, P.E., Allenby, G.M., & McCulloch, R.E. (2005) *Bayesian statistics and marketing*. Wiley: Hoboken, NJ.

Steiner, W., & Hruschka, H. (2003) Genetic algorithms for product design: how well do they really work? *International Journal of Market Research*, 45, 229-240.

Tsafarakis, S. (2016) Redesigning product lines in a period of economic crisis: a hybrid simulated annealing algorithm with crossover. *Annals of Operations Research*, 247, 617-633.