Impact of Types of Functional Relationships, Decisions, and Solutions on the Applicability of Marketing Models

Sönke Albers[1]

Christian-Albrechts-University at Kiel, D-24098 Kiel, Germany

Abstract

I want to complement the review by Leeflang and Wittink (2000) by investigating the impact different marketing models have on actual decision-making. Consumer products companies do not frequently apply optimization models because the profit improvements of the determination of the *optimal level* of a variable like price or advertising budget are small and heavily depend on hardly predictable competitive reactions. Models are more often applied for the *differentiation* of product attributes or prices to serve the needs of different segments, and the *allocation* of a budget or effort across customers. The most influential modeling tool is spreadsheet software like Microsoft Excel and the add-in Solver.

Keywords: Level decisions, Budget allocation, Spreadsheet Optimization, Optimality conditions, Online heuristics

1. Introduction[2]

Leeflang and Wittink (2000) present an article that organizes the different types of marketing models according to a historical perspective into five eras of model building. The five eras are (1) the direct application of existing operations research and management science methods (1950-1965), (2) the adaptation of models to fit marketing problems (1965-1970), (3) the emphasis on implementable models that are acceptable representations of reality and are easy to use (1970-1985), (4) the development of decision support systems (1985-2000), and (5) in the future the growth of new exchange systems. This categorization allows for an excellent overview of what has been developed and achieved over the last 50 years. From their review one also realizes that some models had more impact than others on actual decision-making.

I want to complement their review by classifying the various marketing problems according to the impact models have on actual decision-making. In particular, the impact varies with the following types of decision: (a) the determination of the *optimal level* of a variable like price or advertising budget, (b) the *differentiation* of product attributes or prices to serve the needs of different segments, and (c) the *allocation* of a budget or effort across customers. It is pointed out in section 2 that, due to the flat

[1] Corresponding author. Tel.: +49-431-880-1542; Fax: +49-431-880-1166.
E-mail address: albers@bwl.uni-kiel.de

[2] The author thanks Karen Gedenk, Elko Kleinschmidt, Manfred Krafft, the editor and an anonymous reviewer for valuable comments on previous versions of this commentary.

maximum principle, profit contribution does not vary much with the absolute level of a marketing variable but with the hardly predictable reaction of competitors. Contrary, the differentiation of product offerings and/or prices as well as the allocation of a budget or effort across customers offers substantial room for improvements because managers are overstrained with intuitively finding optimal solutions and the decisions are hardly observable and cannot be easily countered by competitors.

It is therefore not surprising that, according to my experience, consumer goods companies like Unilever, Procter & Gamble and Kraft Jacobs Suchard apply quantitative models very rarely. These companies are, with the exception of promotion decisions, not so much concerned with differentiation and allocation but with optimal levels of marketing instruments. However, there do exist many successful models developed in the area of salesforce management in an industrial context. This is because for these companies decisions on optimal levels of sales expenditures or other budgets are not as important as the many complex decisions on the allocation of effort and/or budgets across customers.

This commentary also complements Leeflang and Wittink's historical perspective by investigating the suitability of the types of solutions those marketing models should provide for the manager. In section 3, it is argued that closed-form solutions and optimization algorithms play a minor role in actual decision-making. The main tool that has made marketing models the rule today rather than the exception is represented by spreadsheet software like Microsoft Excel with its add-ins Solver and @Risk. Excel allows for what-if analyses, scenario analyses, and simulations that are the main applications of marketing models in practice given uncertain competitive reactions and uncertain predictions of the future market developments. However, if we are concerned with differentiation and allocation decisions, then optimality conditions in the form of formulas and heuristics may prove to be valuable.

I agree with Leeflang and Wittink (2000) that in future firms will be more and more concerned with single customer relationships in a one-to-one-marketing environment. This implies that differentiation and allocation aspects will gain even more importance than they already have. In section 4, it is predicted that the application of marketing models similar to salesforce models will increase substantially in the future. Otherwise firms may not be able to cope with the complexity of making optimal one-to-one marketing decisions for thousands of customers. As a result, one can expect that the main challenges of marketing model building still lie ahead.

2. Impact of functional relationships and decision types

2.1 Level versus differentiation decisions

Many marketing models assume certain response functions with exact values for the parameters and no competitive reaction. In this case all types of decisions can be supported by setting up the model and applying appropriate optimization software.

Generally, the number of variables is not very high so that the optimization can be carried out today with spreadsheet software like Microsoft Excel. This involves the application of the add-in optimization tool Solver that has been tested to behave very favorably in comparison to other professional optimization software (Fylstra et al. 1998). The advantage of Excel is that this program is available on nearly all computers, that employees of companies are accustomed to it and that the model building effort is very modest.

The improvements in profit contribution compared to intuitive solutions are typically the smallest for determining the optimal level of a variable and the highest for the differentiation of offerings and the allocation of effort or a budget. Tull et al. (1986) have demonstrated the so-called flat-maximum principle, which implies that the profit contribution resulting from different levels of marketing instruments, e.g. advertising budget, typically varies little. This means that it is simple to arrive at close-to-optimal solutions even if one does not know exactly the response function. This is especially true if one applies the riskless policy of overspending.

In contrast, the determination of optimally differentiated marketing instruments or optimally allocated budgets or efforts proves to be very valuable because managers would be overstrained with intuitively finding optimal solutions (Albers 1996). Almost 20 years ago, McIntyre (1982) showed that allocation decisions are not affected by errors in the response function as long as they do not concern the relative response in comparison to the other allocation units. Chakravarti, Mitchell, and Staelin (1979) have shown that managers have difficulties in estimating the absolute level of response to marketing-instruments but are rather good at estimating relative responses. Therefore, Little and Lodish (1981) conclude that allocation decisions (and the same is true to a lesser extent for differentiation problems) are especially suitable for model building effort.

2.2 Influence of competitive reactions

This evaluation of the suitability of marketing building effort for different types of decisions becomes even more true if one takes into account competitive reactions. Absolute levels of marketing instruments can readily be observed by competitors and are therefore subject to reactions. In contrast, it is much more difficult to observe the differentiation of product offerings or prices across customers or the allocation of a budget or the effort devoted to customers. As a result, a manager concerned with the optimal level of marketing instruments has always to take competitive reactions into account, while neglecting competition in differentiation or allocation decisions may not be very problematic.

Many model builders have tried to incorporate competitive reactions by assuming a certain behavior on the basis of some plausible axioms. The most common assumption is the so-called Nash behavior, which means that a game is in equilibrium when none of the players can improve his situation without hurting the competitor. This Nash-principle has been implemented in many theoretical marketing models. However, empirical investigations give evidence that players do not behave according to the

Nash-solution but overreact in order to reduce a possible asymmetry in achieved profits (Leeflang and Wittink 1996; Marks 1994). As there are no studies available showing that competitive reactions can easily be predicted, firms can only work with what-if or scenario analyses. Note, however, that these analyses only provide information for the manager while he/she then has to decide based on some intuitive assumption on the competitive reaction.

As a consequence, marketing decision models play a rather unimportant role for consumer goods that are directed to the whole market whereas decision support plays a prominent role for all marketing instruments that are directed to individual customers or a large number of segments like in salesforce management. But as we will see in section 4, the principles developed there nowadays also apply to one-to-one-marketing on the Internet with respect to consumer goods.

3. Suitability of types of solutions

A multitude of different marketing models has been developed over the past 50 years which provide different types of solutions for the decision maker. As one can see from Table 1 the solutions encompass closed-form solutions in which only parameter values have to be inserted to arrive at the numerical value of the variable, as well as formulas expressing optimality conditions, what-if-analyses, heuristics and optimal numerical solutions. While closed-form solutions and formulas expressing optimality conditions are mainly based on marginal analysis, heuristics and optimal numerical solutions require specific algorithms.

< please insert Tab. 1 about here >

3.1 Optimization with Excel's Solver

Closed-form solutions have been and still are popular and mainly used for determining the optimal level of a variable. If the outcomes depend on either uncertain response functions or uncertain competitive reactions, then what-if analyses, scenario analyses or simulations may be more appropriate. The application of this kind of analyses took a dramatic increase with the advent of spreadsheet software. The most popular software Excel by Microsoft offers different types of what-if analyses and scenario analyses. Together with the add-in @Risk offered by Palisade it is also possible to simulate the distribution of outcome measures as a result of distributions of parameter values. As already pointed out in the last section, this type of solution is especially helpful in situations where competitive reactions are likely, such as for optimal levels of variables like price and advertising budget. If the decision maker is concerned with more complex decisions like the differentiation of product offerings and prices as well as the allocation of a budget or effort across customers, he/she resorts to heuristics or algorithms that numerically determine the optimal solution. Most marketing problems are inherently nonlinear. As nonlinear optimization software was not readily available until the end of the eighties, numerical optimization did not play an important role. This changed with the development of Excel's Solver that can solve any nonlinear optimization problem with any type of restrictions (Fylstra et al. 1998). This has greatly facilitated the development of nonlinear optimization models. Therefore one may conclude that the development of spreadsheet software like Excel together with the nonlinear optimization add-in Solver has led to more applications of marketing models in practice.

3.2 Closed-form solutions

Given such a powerful tool as Excel's Solver, one may question the usefulness of closed-form solutions. This becomes even more true as closed-form solutions can only be derived for small problems that are mathematically simple enough for marginal analysis. However, closed-form solutions will still play a role in the future because they provide insights into problem structures and optimal solutions. A good example is the problem of determining the optimal fixed salary and commission rate for a salesperson. The basic model has been developed by Basu et al. (1985) who provided optimality conditions. If one wants to arrive at a closed-form solution one has to work with prespecified compensation functions such as a fixed salary and a linear commission rate. If one assumes that commission income depending on sales effort is gamma distributed and that the risk utility function for the salesperson is given simply by expected commission income minus the weighted standard deviation of the gamma distributed commission income, then the optimal solution provides a negative fixed salary for realistic parameter values (Albers, 1995). Thus, only closed-form solutions provide the insight that, for example, the well-known approach by Basu et al. (1985) must have some defects and should be extended by other model components to be able to arrive at plausible solutions.

3.3 Optimality conditions

Now, turning to optimality conditions, I find the following equations derived from the theorem by Dorfman and Steiner (1954) very helpful for practical applications although this theorem is already 46 years old.

$$(1)\qquad \frac{\text{Optimal marketing budget}}{\text{Profit contribution before marketing cost}} = \text{Marketing - budget elasticity}$$

$$(2)\qquad \frac{\text{Optimal marketing budget}}{\text{Revenue}} = \frac{\text{Marketing - budget elasticity}}{\text{Price elasticity}}$$

These formulas can be used for assessing what kind of elasticities management may have assumed in the current situation. By computing the left-hand sides of equations (1) and (2), one can compare the assumed elasticities to the values of meta-analyses in order to see whether the assumptions make sense. With average elasticities in mind one can also assess whether the marketing-budget spending is effective.

For example, these ideas have been used for the assessment of cooperations where only accounting data were available. Albers (2000) described the problem that a company faces if it wants to cooperate with another company to run a joint salesforce.

In order to determine whether it would benefit from such a cooperation or not, the company must know the elasticity of sales with respect to sales force effort of the prospective partner. Knowing only data like the salesforce budget as well as the advertising budget relative to profit contribution, Albers proposed to assume that the companies operate close to the optimum which allows to infer the elasticities from (1) and (2). With these elasticities it is, then, possible for a company to evaluate what it would gain from a cooperation under different rules for sharing the profit.

3.4 Heuristics

Optimality conditions are also very helpful for deriving heuristics for the allocation of a budget or effort across customers. Albers (1997) showed that, in the optimum, a marketing budget should be allocated across customers in proportion to the (mathematical) product of gross margin, revenue, and marketing budget elasticity. This principle has also been used in a more complex algorithm for solving the sales territory alignment problem (Skiera and Albers 1998). Albers (1997) found that the application of this formula with the current values for profits and elasticities for several periods leads to solutions that converge to the optimum very quickly. This means that in practice decision makers no longer need to be concerned with the application of optimization software. Rather they can apply this simple allocation rule and only have to estimate the respective elasticity values.

Heuristics have been undervalued for a long time. Given the fact that practitioners rarely apply optimization principles, heuristics could be tremendously helpful. In addition, the decision maker does not have to follow a policy proposed by a black-box model that he/she does not understand. And finally, with the advent of the Internet, more and more decisions will become online decisions. For example, if a certain customer is calling a certain Internet website the system must decide, based on past performance, how much effort and/or budget to spend on this customer. Such online decisions require nearly instantaneous responses that do not allow for the application of time-consuming optimization procedures. Therefore, future research should focus more on near-optimal heuristics.

Managers also hesitate to apply optimization procedures because they are not sure whether a certain optimal solution will also hold for different parameter values of the customer response function. It is therefore not sufficient to compute the optimal solution. Rather, we also have to find out whether decision models lead to superior solutions. Authors have to deal more with investigations that show that their optimal solutions are still optimal even if parameter values have been estimated incorrectly. Such analysis has been provided for example by Skiera and Albers (1998) for their model COSTA. They showed that even in the case of extreme misestimation of elasticities, COSTA provides better solutions than an equal potential approach given the same false response functions for both approaches.

4. Future trend of customer orientation

I agree with Leeflang and Wittink (2000) that we will experience a shift in the focus from products to customers in the future. This is due to the fact that more and more consumers will use the Internet and shop there. In online environments, customers can truly be treated as individuals because data of all transactions can be stored and could allow for a precise and detailed estimation of individual responses. This implies that the principles of differentiation and allocation will become dominant.

While in the offline world too many different offerings are not operational we can offer personalized products or assortments at personalized prices on the Internet. Firms will have individual relationships with consumers and therefore can determine the optimal effort (money and time) they should devote to individual customers. As budgets and time are restricted this will involve the solution of allocation problems in the form of a continuous stream of decisions.

Personalized offerings are advantageous because, theoretically, such offerings allow to absorb the whole consumer surplus. This implies that we no longer need market research that provides information about the most preferred product. Rather, we need methods how to differentiate the offered products and services and the respective prices such that the consumer chooses by him-/herself the product according to his/her willingness-to-pay. This is called versioning (Shapiro and Varian, 1999, p. 53 ff.). If the prices cannot be differentiated together with a versioning of products, companies have to take advantage of personalized prices like in auctions (ebay.com) and reverse auctions (priceline.com). The question is then which part of the total offer should be auctioned and which one offered at fixed but differentiated prices. If the company also faces capacity restrictions as is the case for hotels and flights, it has to apply principles of yield management (Weatherford and Bodily, 1992) in order to absorb consumer surplus. So far, we discussed the differentiation of just one product or service. However, in most situations the firm also faces the problem to recommend other parts of its assortment. Here, we need recommendation agents that have to infer the utility function of a customer in order to be able to provide a valuable recommendation. Since we have to satisfy the individual needs of a customer we have to develop methods that infer individual utility functions with few degrees of freedom where the objective is no longer to maximize the statistical fit but the satisfaction of the individual customer. This is done, for example, by collaborative filtering and web-sites like personalogic.com.

Another field will be the prediction of the probability that a certain customer will buy again at a certain point of time. Depending on his transaction history models have to be developed that will allow to recommend with how much effort the customer should be treated. Models already developed in the context of mail-order marketing (Schmittlein and Petersen, 1994) are too complex to be applied instantaneously in online-environments on a continuous basis. Segmentation of customers as in the industrial context may help. A prerequisite is sound life-cycle costing providing profit contribution figures per customer. However, in online-environments direct costs are negligible. In addition, there may be joint revenues of buying communities as well as cost that can be allocated only to a whole network but not to a single member of this network. Research would be very helpful that resolves issues of allocating revenues and costs such that the firm makes the right decisions.

Given the complexity of such decisions that have to be made routinely for thousands of customers in an online environment one can easily predict that the future of marketing models still lies ahead. And we will probably observe a revival of many models originally developed for industrial markets with their known customers for application in consumer goods markets or service markets.

References

Albers, S., 1995. Optimales Verhältnis zwischen Festgehalt und erfolgsabhängiger Entlohnung bei Verkaufsaußendienstmitarbeitern. Zeitschrift für betriebswirtschaftliche Forschung 47, 124-142.

Albers, S., 1996. CAPPLAN: A decision support system for planning the pricing and sales effort policy of a salesforce. European Journal of Marketing 30 (7), 68-82.

Albers, S., 1997. Rules for the allocation of a marketing budget across products or market segments. In: Arnott, D. et al. (eds.): Marketing: Progress, prospects, perspectives, Proceedings of the 26th EMAC Conference, 20th - 23rd May 1997, Warwick Business School, 1-17.

Albers, S., 2000. Optimal allocation of profit across companies operating with a joint salesforce. OR Spektrum 22, 19-33.

Basu, A.K., Lal, R., Srinivasan, V., Staelin, R., 1985. Salesforce compensation plans: An agency theoretic perspective. Marketing Science 4, 267-291.

Chakravarti, D., Mitchell, A., Staelin, R., 1979. Judgment based marketing decision models: An experimental investigation of the decision calculus approach. Management Science 25, 251-262.

Dorfman, R., Steiner, P.O., 1954. Optimal advertising and optimal quality. American Economic Review 44, 826-836.

Fylstra, D., Lasdon, L., Watson, J, Waren, A., 1998. Design and use of the Microsoft Excel Solver. Interfaces 28 (5), 29-55.

Leeflang, P.S.H., Wittink, D.R., 1996. Competitive reaction versus consumer response: Do managers overreact?. International Journal of Research in Marketing 13, 103-119.

Leeflang, P.S.H., Wittink, D.R., 2000. Building models for marketing decisions: Past, present and future. International Journal of Research in Marketing 17 (this issue).

Little, J.D.C., Lodish, L.M., 1981. Commentary on judgment based marketing models. Journal of Marketing 45 (Fall), 24-29.

Marks, U.G., 1994. Neuproduktpositionierung in Wettbewerbsmärkten. Deutscher Universitätsverlag: Wiesbaden.

McIntyre, S.H., 1982. An experimental study of the impact of judgment-based marketing models. Management Science 28, 17-33.

Schmittlein, D.C., Peterson, R.A., 1994. Customer base analysis: An industrial purchase process application. Marketing Science 13, 41-67.

Shapiro, C., Varian, H.R., 1999. Information rules. A strategic guide to the network economy. Harvard Business School Press, Boston, MA.

Skiera, B., Albers, S., 1998. COSTA: Contribution optimizing sales territory alignment. Marketing Science 17, 196-213.

Tull, D.S., Wood, Van R., Duhan, D., Gillpatrick, T., Robertson, K.R., Helgeson, J.G., 1986. „Leveraged“ decision making in advertising: The flat maximum principle and its implications. Journal of Marketing Research 23, 25-32.

Weatherford, L.R., Bodily, S.E., 1992. A taxonomy and research overview of perishable-asset revenue management: Yield management, overbooking, and pricing. Operations Research 40, 831-844.

Type of solution	Tools	Suitable for Purpose
Closed-form solution	Marginal analysis	Insights into problem structures
Optimality condition	Marginal analysis	Performance assessment Inference of elasticities
What-if analysis, Simulation	Excel (Spreadsheets) @Risk (Add-in)	Outcomes depending on uncertain response function, competitive reactions and environments
Heuristic	Marginal analysis together with Excel (Spreadsheets)	Support of complex decisions
Optimal numerical solution	Excel-Solver Standard optimization software	Support of decisions in stable and certain environments with no time pressure

Table 1: Suitability of different types of solutions for different types of purposes