

# 4 The Interface of Marketing and Operations Research

Berend Wierenga, Rotterdam School of Management, Erasmus University, [bwierenga@rsm.nl](mailto:bwierenga@rsm.nl)

## Abstract

The transition of marketing, in the 1960's, from a focus on distribution processes to a functional area of management, created a lot of opportunities for the use of operations research (OR) in marketing. Originally the direct application of OR techniques to marketing problems was prominent, later marketing models developed as an independent field within marketing itself, but keeping a continuing interface with OR. We discuss the most important areas where OR has been influential in marketing: optimization, stochastic processes, and decision support systems. More recently, the customer-centric approach in marketing has caused a renewed need for the use of OR-methods in marketing, especially in the areas of customer relationship management (CRM), online marketing and viral marketing.

## 4.1 Introduction

Operations research (OR) is the discipline of Jo van Nunen, and my academic life has been devoted to marketing. The interface between these two fields is interesting and important. This is the case when we look at research, but also in teaching and student projects there are many subjects where marketing and operations research overlap. This is especially relevant in the context of a business school, such as the Rotterdam School of Management, where Jo and I have been colleagues for over twenty-five years. Interestingly, early in his career, Jo van Nunen made a few excursions into marketing, applying Markov programming to advertising campaigns and sales promotions (van Nunen 1972; 1975), but later on he seems to have left the marketing-OR interface to others. However, the field of physical distribution and logistics, where Jo has done most of his research, is close to marketing.

In this contribution, I approach the interface of marketing and operations research from the perspective of my own field, marketing. Operations research/management science has played an important role in the development of marketing, especially in the early years. The emergence of marketing models, now one of the most important areas in marketing was strongly stimulated by OR. I do not have a good idea of the influence of marketing on OR, but at least some famous OR subjects such as the traveling salesman problem and the bullwhip effect are inspired by marketing phenomena. However, there is not a specific subarea within OR dealing with marketing problems. From the marketing perspective, we look at OR as a supplier of important techniques, especially optimization, that we can use for solving marketing problems. Most of the substantive quantitative work in marketing, for example in the area of marketing models, takes place within marketing itself. Besides its role as a supplier of interesting problems, marketing can also be useful for OR in another sense, when we see the recent efforts of the OR community to increase the demand for its contributions and to improve the image of OR ("The Science of Better").

In the paper I take a broad interpretation of operations research, and include information and decision support systems issues. This is fully in the spirit of Jo van Nunen who was more interested in solving problems than in the precise demarcations between the different subfields covered by his chair.

## 4.2 Developments in marketing

Marketing as a field started around 1900. In the first sixty years of its existence, it can best be characterized as a branch of applied economics. During that period, marketing followed a primarily descriptive approach, studying the flow of goods from the original producer (e.g. the farmer) to the ultimate (end) consumer purchasing the final product in the store.

Marketing paid attention to all what happened in this distribution process, including grading, storing, processing, transporting and the exchanges between different parties in the distribution channel. In this primarily descriptive phase of marketing, there was not much need for optimization.

However, in the 1960's marketing went through a major change, marked by the invention of the marketing concept and the marketing mix. The marketing concept implied that the wants and needs of the customers should guide every business decision. With the marketing mix, marketers received a set of instruments that they could use to influence the position of their product and brands in the market. So, the supplier of a product did not have to passively stand by anymore, watching what happened to his product in the market place, but could play a managing role, that is "manage his product" (Hence job descriptions such as "product manager" and "brand manager"). Marketing became *marketing management* and since that time is one of the most prominent functional areas of management in a company. With respect to the marketing mix, the so-called "four P's": product, price, promotion, and place, are very well known. With these instruments a marketer, on the one hand can increase the demand for his product, for example by improving the quality of the product, by lowering the price, by spending on advertising and sales promotions, or by making the product more easily available for the consumer. On the other hand, all these marketing efforts and actions cost money, and the question is: what is the optimal marketing mix, given the different demand and cost effects? In other words, for what values of the marketing mix variables do we obtain the highest profit? It is clear that we have an optimization problem here, and OR should be able to help.

Optimization requires an analytical approach to marketing problems and therefore it was not by accident that in the 1960's three prominent books were published on a quantitative approaches to marketing : Bass et al. (1961), Frank, Kuehn and Massy (1962), and Buzzel (1964). These books introduced the concept of marketing models, discussed their advantages, and gave examples of how marketing models can be implemented and used in marketing domains such as advertising, media planning, pricing, sales force allocation, forecasting and inventory control. They marked the beginning of an explicit analytical approach to marketing decision making. However, the transition from marketing to marketing management is not the only factor that explains the move towards a more quantitative approach in marketing (Wierenga 2008). Probably, the most determining factor was the quickly rising popularity of operations research/management science in those days. The sixties were the heydays of operations research (OR), also called Management Science (MS). Operations research started as a field that developed mathematical tools to support military operations in the Second World War (especially for logistics and transportation), and later became a modeling and optimization field with applications in virtually all areas of society. OR/MS became particularly important in the domain of business. ORSA and TIMS, the predecessors of the current professional association INFORMS, were founded in 1952 and 1953, respectively. Marketing quickly recognized the potential of OR for marketing decision making and OR has been a major driving force behind the start of the field of marketing models, later also referred to as marketing science. This occurred about ten years after the start of OR/MS.

We will now discuss three topics that have been important in the history of the marketing-OR interface.: optimization, stochastic processes, and decision support systems. Next, we will discuss new opportunities for intensifying the marketing-OR interface.

### **4.3 Optimization**

The most complete treatment of a model building approach to marketing decision making is provided by Kotler (1971). He starts out by formulating a marketing decision as a mathematical programming problem (p 16), where the marketing decision variables have to be set in such a way, that some goal variable, or a set of goal variables are maximized, within a set of constraints. Marketing decision variables are the marketing mix instruments. Goal variables can be profit, sales, market share, or some utility function representing the preferences of relevant actors, for example, management, shareholders, or employees. Constraints can be budget limitations (for example a limited advertising budget), a priori limits for the values of certain decision variables (e.g. a lower limit on the price) and capacity restrictions, for example manufacturing capacity or short term sales force capacity. In

principle, such a mathematical program can be solved using the appropriate OR techniques. This was very much the approach in the early days of marketing models. In their two volumes on management science in marketing Montgomery and Urban (1969 and 1970) describe a large number of marketing problems that can be approached with OR techniques, such as determining the advertising budget, specification of the media schedule (mediaplanning), pricing decisions, distribution decisions, personal selling, and new product decisions. The mathematical programming techniques employed for solving these problems are: linear programming, integer programming, goal programming, dynamic programming, nonlinear programming and stochastic programming. However, this stage of just taking an optimization technique from OR and looking for problems in marketing that could be solved with it, ended soon. In the 1970's, the field of marketing models grew exponentially and, what is perhaps more important, developed an identity of its own (Wierenga 2008). The modeling of marketing phenomena and marketing problems became interesting in itself, irrespective of whether or not they could be solved with a known OR technique. In the sixties it was often a matter of a technique seeking for a task, whereas now the marketing problems as such became the point of departure. Researchers started to realize that OR algorithms can be too much of a straightjacket for real world marketing problems. Sometimes marketing problems had to be "mutilated" in order to fit them to an existing OR technique (Montgomery and Weinberg 1973). The most conspicuous example is the application of linear programming to media planning (Engel and Warshaw 1964). Media-planning problems are not really linear, but were forced to be so, in order to solve them with linear programming. So, marketing models became a field independent from OR and has remained that way ever since. This is also exemplified by the start (in 1982) of a modeling journal, dedicated to the field of marketing, *Marketing Science*, which is now one of the prominent INFORMS journals. Most attention in the seventies was devoted to models for marketing mix instruments (for example models for advertising, price, and personal selling). The issue was how to model the relationship between a particular marketing instrument and sales, i.e., to specify so-called marketing response models, with much attention for the mathematical form of this relationship (e.g., linear, concave, or S-shaped (Kotler 1971). The next issue was how to estimate these response functions from empirical data. This is where econometrics came in (Naert and Leeflang 1978).

In the seventies we also saw the take-off of "labeled models". A labeled model typically works in three steps: (i) a specific mathematical structure (model) for a particular marketing phenomenon is proposed; (ii) this model is coded in a computer program, and (iii) this program is used for marketing decision making, e.g., for predicting the outcomes of alternative marketing actions or for optimizing marketing efforts. It became fashionable to give a specific label or name to such a model, often an acronym that expressed its purpose. Well-known examples are: CALLPLAN (Lodish 1971) for the planning of sales call decisions, ADMOD (Aaker 1975) for media planning in advertising, and ASSESSOR (Silk and Urban 1978) for new product decisions. Many of these labels have become "icons" in the marketing models field.

#### 4.4 Stochastic processes

Besides optimization techniques, stochastic processes have always been a prominent area of operations research (Hillier and Lieberman 2010). In marketing this branch of OR has seen a lot of applications too. In the sixties and seventies of the last century, there was a lot of interest for stochastic brand choice models (Massy, Montgomery and Morrison 1970; Wierenga 1974). Here the interest is in the brand(s) that a consumer chooses when making consecutive purchases in a product class.

When we follow the purchases of a consumer in a certain product category, for example beer, over time, we can consider the probability that this consumer chooses brand  $i$  at purchase occasion  $t$ . Let this probability be denoted as  $p_{it}$ . Now, it is interesting to formulate models for  $p_{it}$ . For example, when  $p_{it}$  is constant and independent of  $t$ , we call the brand choice process a zero-order Bernoulli process. There are two variants of this Bernoulli process: one where the purchase probability to purchase brand  $i$ ,  $p_i$  is identical for all customers (the homogeneous Bernoulli model) and the other where different consumers can have different values for  $p_i$  (the heterogeneous Bernoulli model). In the

case of the heterogeneous Bernoulli model it is interesting to know the distribution of  $p_i$  in the consumer population. If only two brands are distinguished in the market (for example the focal brand and “all others”), a beta distribution can be used for this purpose. In the multibrand situation ( $>2$  brands) a Dirichlet distribution can be employed.

Bernoulli models are zero-order, implying that there is no purchase feedback. Purchase feedback would imply that the probability to purchase a specific brand is affected by previous purchases. For example, after the purchase of brand  $i$ , the consumer might be very satisfied with that brand, which would imply that at the next purchase the probability of choosing brand  $i$  has increased. To model this phenomenon a Markov model is very appropriate, with the purchase histories as states. Markov models are also very prominent in OR. For example with a first order Markov model, we look at transition probabilities of the type  $p_{ij}$ , that is the probability to go from brand  $i$  to brand  $j$ , or the probability to purchase brand  $j$ , given that the most recent purchase was brand  $i$ . For example, what is the probability that a consumer chooses Amstel, if he chose Heineken at the previous beer purchase? In empirical analyses one typically finds transition matrices with relatively large values on the diagonal, which can be interpreted as brand loyalty: after the purchase of a certain brand, there is a high probability to purchase that brand again. With first order Markov models, only the most recent part of the purchase history (the previous purchase) is relevant. If the brand choice process has a longer memory, we can use higher order Markov chains. For example, with a second-order Markov chain, the two most recent purchases are relevant.

Stochastic models are used in marketing not only for brand choice (choice of the brand given that the product is bought), but also for purchase incidence, that is to model when purchases are made. There is a renewed interest in that type of models in the context of CRM (customer relationship management). We will discuss CRM at greater length later in this paper. In CRM we want to compute the value of a customer, given his observed purchasing behavior so far. An example of a stochastic model used for that purpose is the NBD/Pareto model, developed by Schmittlein, Morrison and Colombo (1987). The model assumes that consumers are active (i.e. make purchases) during some period of time, and then become inactive. While active, they make purchases following a Poisson process with rate  $\lambda$ . The parameter  $\lambda$  is distributed over the consumer population according to a two-parameter gamma distribution. Customers are active during a limited period of time following an exponential distribution with a death rate of  $\mu$ . The distribution of  $\mu$  in the consumer population is again a two-parameter gamma distribution. With the NBD/Pareto model, only a few observations of a consumer's purchase history are needed in order to predict the likelihood that this consumer is still active. The NBD/Pareto model and recent variants of it (Fader, Hardy and Lee 2005) are important tools in CRM. In the context of CRM we also see renewed use of Markov chains, for example with the states defined as recency states (Pfeifer and Carraway 2000).

For example, state 1 could mean: the most recent purchase occurred in the last period; state 2: the most recent purchase occurred in the last but one period, etc. Stochastic models for CRM is a hot area in marketing these days.

## 4.5 Decision Support Systems

Originally there was a lot of optimism about the use of optimization techniques and mathematical models in marketing. With marketing models, it seemed, marketing would almost become a scientific activity. Kotler (1971) opens his classical book on marketing models, with the statement: “Marketing operations are one of the last phases of business management to come under scientific scrutiny” (p. 1). Some people expected that marketing decision making would just become a matter of formulating a marketing problem as a mathematical programming problem, and then solve it with one of the known techniques of operations research. But the harsh reality was that the actual application of marketing models to real-life problems in companies remained far below expectations. This has caused a tradition of complaints in the marketing literature, ranging from “The big problem with marketing science models is, that managers practically never use them” (Little 1970) to (thirty years later) “Maybe there is some level of maturity in the technology, but I cannot see much evidence in the application” (Roberts 2000). Recently, Lilien and Rangaswamy (2008) referred to “the gap between

realized and actual potential for the application of marketing models". Marketing is not unique as a field of management where decision makers are reluctant to base their decisions on the recommendations of mathematical models. It was realized that many problems in management are not sufficiently structured for the straightforward application of optimization techniques. Therefore, the concept of *decision support systems* was developed, primarily aiming at semi-structured tasks, with the purpose of supporting, rather than replacing managerial judgment, and improving the effectiveness of decision making, rather than its efficiency (Keen and Scott Morton 1978). In marketing there are many of these semi-structured tasks, and it is not surprising that soon after their introduction in the management science/information systems field, decision support systems also entered the field of marketing (Little 1979). Little defined a marketing decision support system (MDSS) as a "coordinated collection of data, systems, tools and techniques with supporting software and hardware by which an organization gathers and interprets relevant information from business and environment and turns it into an environment for marketing action" (p. 11). Little's concept of an MDSS was much more than a marketing information system. Important elements were models, statistics, and optimization, and the emphasis was on response analysis; for example, how sales respond to promotions. In Little's view, MDSS were suitable for structured and semi-structured marketing problems, had a quantitative orientation and were data-driven. Almost two decades later, Wierenga and Van Bruggen (1997; 2000) presented a classification of marketing decision support technologies and tools, and used the term "marketing management support systems" to refer to the complete set of marketing decision aids. They define a marketing management support system (MMSS) as "any device combining (1) information technology, (2) analytical capabilities, (3) marketing data, and (4) marketing knowledge, made available to one or more marketing decision makers, with the objective to improve the quality of marketing management". Marketing management support systems is a comprehensive term which includes the primarily quantitative, data-driven marketing decision support systems (for structured and semi-structured problem areas) as well as support technologies that are aimed at supporting marketing decision-making in weakly-structured areas. The latter are primarily qualitative, and knowledge-driven.

Marketing models represent the analytical component of a marketing management support system, and often constitute the core (engine) of such a system. However, people soon realized that you need more than an engine to make a car run. Besides a technically correctly working model, a successful MMSS also needs attractive design characteristics, for example the system should be easy to operate, have a nice user interface, and should be flexible and adaptive.

Furthermore, ample attention should be paid to the implementation of the MMSS in the organization. Top management support, user involvement in the implementation process, communication, and training are important. In the decision support literature in marketing much attention is paid to these "demand-side" elements, including a good match between the so-called marketing problem-solving mode and the decision support technology being used (Wierenga and van Bruggen 2000; Wierenga, van Bruggen and Staelin 1999). For example, when the marketing problem-solving mode is optimizing, it is clear that some OR technique is the best decision support technology. However, for the marketing problem-solving mode of analogizing, a support technology based on analogical reasoning, for example case-based reasoning (CBR) makes more sense.

A recently developed MMSS for the movie industry can illustrate these concepts (Eliashberg, Hegie, Ho, Huisman, Miller, Swami, Weinberg, and Wierenga 2009). The problem was to develop a support system that can help the programming departments of a movie theater company to make weekly movie schedules for their cinemas. Especially for large multiplexes with many different screens the construction of such schedules is a complex problem. The analytical core of the developed system ("SilverScheduler") consists of two parts. One is the forecasting module, that makes conditional forecasts of the number of visitors for each possible show (if a particular movie is shown on a particular day at a particular time). These forecasts are made with a model estimated on observations of visitors data.

The second analytical component is the scheduling algorithm, which searches for the best schedule (in terms of total visitor numbers) given the availability of screening rooms, their seating capacities, and

other constraints, such as cleaning times, prevention of crowding, etc. For the scheduling algorithm a column generation procedure was employed (Barnhart, et.al 1998). This movie-scheduling system is clearly a combination of approaches from marketing (demand forecasting) and OR (finding the best schedule). As is the case for many decision support system in marketing, developing the analytical core of the system (the forecasting and the scheduling module) is only part of the story. Much effort was put in building an attractive interface, where the user can shift movies around and do fine-tuning of the schedules. From the start to the end, there was a lot of user involvement during the implementation, and top management played a very supporting role. Furthermore, the synergy between the MMSS and the users is important. For example, for new movies the expertise of the movie theater employees is used. For a new movie they give their intuitive judgments about the similarity with earlier movies, and this information is used to forecast the visitors of this new movie.

In hindsight, for marketers it should not have come as a surprise that the supply of sophisticated marketing models did not automatically generate demand for such models. Marketing models have to be adopted and used by decision-makers in organizations, and marketers are just like other people with their resistance to change and to new ways of doing things. Given this state of affairs, it became important to have more insight in the role of these “people issues” and, at a more general level, in the factors that can stimulate (or block, for that matter) the adoption and use of marketing management support tools. This gave rise to systematic research (cross-section studies, field studies, lab experiments, field experiments) on these issues. The knowledge acquired can be found in the marketing management support systems literature. “Marketing management support systems” does not just refer to a collection of decision support systems and technologies, but also to a substantive field with an emerging body-of-knowledge about the factors and conditions that affect the adoption, use, and impact of marketing decision support tools in organizations. Many of the findings in this field are not just relevant for marketing management support systems, but also for decision support systems in other domains. Interested readers are referred to Wierenga, van Bruggen, and Althuizen (2008) and Van Bruggen and Wierenga (2010).

## **4.6 New opportunities for intensifying the marketing-OR interface**

### **4.6.1 Customer-centric marketing**

Earlier I mentioned that the transition – in the 1960’s- of marketing from a descriptive field to marketing management created many opportunities for optimization approaches in marketing. At this moment marketing is going through another transition, that is from product management to management of individual customers, which can be denoted as *customer-centric marketing*. There is a switch from the focus on groups of customers (“markets”) to the focus on individual customers. Customer-centric marketing can be considered as the third era of marketing, after marketing as distribution (1900-1960) and marketing as marketing management (1960-2000). Customer-centric marketing has become possible because of the dramatic progress in information technology. Information technology has made it easy to collect and retain information about individual customers. This is not only demographic information (e.g., family status, age, and education) but also information about their purchase histories, and their responses to marketing campaigns. Whereas the typical product management type of marketing basically aims at groups of anonymous customers (with their characteristics only know at the level of the group, for example a specific market segment), in customer-centric marketing individual customers are no longer anonymous, have their own identity and can be targeted individually. Customer-centric marketing requires new marketing metrics, such as, customer share, customer satisfaction, and customer lifetime value (CLV). Customer-centric marketing also causes a shift in the focus of marketing management support systems, where data are increasingly organized around individual consumers.

From the perspective of MMSS, the transition to the third marketing era is a very important development. The individual customer data have also stimulated the development of all kinds of new types of marketing models, which can be used to optimize marketing efforts at the level of the individual customers We will now briefly discuss three topics that are directly related to customer-centric marketing.

#### **4.6.2 Customer Relationship Management**

Customer-centric marketing has stimulated the development of customer relationship management (CRM) systems. A CRM system is a computer system with a data base containing data about customers, about company-customer contacts, and data about the customers' purchase history. (Van Bruggen and Wierenga 2010). Recently, companies have been installing CRM systems at a high rate and many companies now have functioning CRM systems in place. There are enormous opportunities for analyzing customer behavior and optimization of marketing decisions with the data in CRM systems. An example of a frequently employed methodology is data mining. With data mining a prediction model (e.g., a neural net) is trained to learn the association between customer characteristics (for example, demographical information and purchase history) and interesting dependent variables (for example, whether or not the customer has accepted a specific offer). Once the model has been trained, it can be used to predict whether other customers (with known characteristics) would accept the offer. This technology is typically used in marketing campaigns to select those customers from a database that have a high probability of accepting a particular offer. Data mining can cause large savings, because of a better allocation of expensive marketing resources. Many questions can be answered with the intelligent use of the data in CRM systems, such as: which customers should we acquire, which customers should we retain, and which customers should we grow (Reinartz and Venkatesan 2008)? Related issues studied recently are: which customers will be "alive" (i.e., still buying) at a certain point in time (see our discussion of stochastic processes) and how can we predict customer "churn", i.e., the probability that a customer with a known purchase history will defect?. There are many opportunities here for model building and optimization. With information available about purchasing behavior and preferences of individual customers, the goal is to make those offers and send those messages to individual customers that are most cost/effective. OR methods can help here to allocate marketing budgets in optimal way. Since the number of individual customers is mostly large, it is clear that we need automated systems here

#### **4.6.3 Online marketing**

Also the development of online marketing (or "e-commerce") creates new opportunities for synergy between marketing and OR. In online marketing there are two major questions. First, which customers will order how much from the assortment offered in the online shop in a given period? Second, what is the most efficient logistical operation to get the ordered products to the customers? The first question is a marketing problem, the second one is an OR problem. Therefore in online marketing selling and distributing are closely intertwined, and optimization here should be the joint optimization of marketing *and* physical distribution. It does not make sense if marketing tries to make its offerings to appeal maximally to the wishes of the individual customers, if the costs of getting the products to these customers are prohibitive. On the other hand, optimizing the logistical processes of, an online shop is of limited utility, if the (marketing) margins on the different products are not taken into account.

#### **4.6.4 Viral marketing**

In a viral marketing campaign, a organization develops a marketing message and encourages customers to forward this message to its contacts (Van der Lans, van Bruggen, Eliashberg, and Wierenga 2010). This is a way to spread information in a consumer population in a fast and cost-effective way. Consumers can receive message from different sources, for example emails from the organization behind the viral campaign ("seeding emails"), banners and offline advertisements, and emails from other customers (friends) with the invitation to participate in the campaign. Crucial parameters in a viral campaign are the probabilities to participate in the campaign, given the receipt of the different messages as just described, and the number of friends to whom the message is forwarded after participating.

These parameters are used in the so-called viral-branching equations to predict the total numbers of participants reached in the campaign in specific time intervals since the start of the campaign. Clearly, there are interesting optimization issues here, for example how to allocate the budget over different

options for starting the campaign (e.g. banners, offline advertising, purchasing addresses for seeding emails) and how to speed up the process. If participants can give feedback to the company, or can order something, it is also important to determine the optimal capacity for handling this feedback, give the predicted response stream.

#### **4.7 Conclusion and perspectives**

During the last fifty years the interface with OR/Management Science has been very important for marketing. In the early years the direct application of OR methods in the domain of marketing was prominent. Later, when marketing models became more of a field of its own, input from OR remained important. The main areas of these inputs are: optimization, stochastic processes and decision support systems. The new emphasis in marketing on a customer-centric approach is creating a lot of new possibilities the marketing-OR interface, for example in CRM, online marketing, and viral marketing. I hope that marketing problems will continue to attract and challenge many of our OR colleagues, to the benefit of both marketing and OR. There are important opportunities, if not necessities for intensifying the marketing-OR interface.

#### **References**

- Aaker, D.A. (1975). ADMOD: an Advertising Decision Model. *Journal of Marketing*, 12 (1), 37-45.
- Barnhart, C., E.L. Johnson, G.L. Nemhauser, M.P.W. Savelsbergh, and P.H. Vance (1998). Branch-and-Price: Column generation for solving huge integer programs, *Operations Research*, 46, 316-329
- Bass, F.M., R.D. Buzzel, M.R. Greene et al., eds. (1961). *Mathematical Models and Methods in Marketing*. Homewood, Irwin, IL.
- Buzzel, R.D. (1964). *Mathematical Models and Marketing Management*. Harvard University, Division of Research, Boston, MA.
- Eliashberg, J., Q. Hegie, J. Ho, D. Huisman, S.J. Miller, S. Swami, C.B. Weinberg, and B. Wierenga. (2009). "Demand-Driven Scheduling of Movies in a Multiplex". *International Journal of Research in Marketing*, 26 (2), 75-88.
- Engel, J.F. and M.R. Warshaw (1964) Allocating Advertising Dollars by Linear Programming. *Journal of Advertising Research*, 4, 42-48.
- Fader, Peter S., Bruce G.S. Hardie, and Ka Lok Lee (2005), "'Counting Your Customers the Easy Way: An Alternative to the Pareto/NBD Model,'" *Marketing Science*, 24 (Spring), 275-284.
- Frank, R.E., A.A. Kuehn, W.F. Massy, eds.(1962). *Quantitative Techniques in Marketing Analyses*. Irwin, Homewood, IL.
- Hillier, F.S. and G.J. Lieberman (2010). *Introduction to Operations Research*, Ninth Edition. Boston: Mc Graw Hill.
- Keen, P.G.W. and M.S. Scott Morton (1978) *Decision Support Systems: an Organizational Perspective*. Reading MA; Addison-Wesley, 264 p.
- Kotler, Ph. (1971). *Marketing Decision Making: A Model Building Approach*. Holt, Rinehart, and Winston, New York, NY, 720 p.
- Lilien, G.L. and A. Rangaswamy (2008) *Marketing Engineering: Models that Connect with Practice*. In B. Wierenga (Ed): *Handbook of Marketing Decision Models*. New York: Springer, 527-559.
- Little, J.D.C. (1970). *Models and Managers: The Concept of A Decision Calculus*. *Management Science*, 16, B466-B485.
- Little, J.D.C. (1979). *Decision Support Systems for Marketing Managers*. *Journal of Marketing*, 43 (3), 9-26.



- Lodish, L.M. (1971). CALLPLAN: An Interactive Salesman's Call Planning System. *Management Science*, 18 (no. 4 Part II), 25-40.
- Massy, W.F., D.B. Montgomery, and D.G. Morrison. (1970). *Stochastic Models of Buying Behavior*. M.I.T. Press, Boston, MA.
- Montgomery, D.B. and C.B. Weinberg. (1973). Modeling Marketing Phenomena: A Managerial Perspective. *Journal of Contemporary Business*, Autumn, 17-43.
- Montgomery, D.B., G.L. Urban.(1969). *Management Science in Marketing*. Prentice Hall, Englewood Cliffs, NJ.
- Montgomery, D.B. and G.L. Urban, eds. (1970). *Applications of Management Sciences in Marketing*. Prentice Hall, Englewood Cliffs, NJ.
- Naert, P.A. and P.S.H. Leeflang (1978) *Building Implementable Marketing Models*. Leiden: Martinus Nijhoff.
- Nunen, J.A.E.E. van, Wessels, J. (1975) Dynamic planning of sales promotions by Markov programming - Proceedings XX International Meeting of the Institute of Management Sciences, Jerusalem, Academic Press 1975, Vol. I, pp. 737-742
- Nunen, J.A.E.E. van (1972) Markov programming for Planning Advertising Campaigns (in Dutch) - Mededelingen Operationele Research, pp. 37-43.
- Pfeifer, P.E. and R.L. Carraway (2000) Modeling Customer Relationships as Markov Chains. *Journal of Interactive Marketing*, 14 (2), 43-55.
- Reinartz, W.J. and R. Venkatesan (2008). DecisionModels for Customer Relationship Management. In B. Wierenga (Ed) *Handbook of Marketing Decision Models*, New York: Springer, 291-326.
- Roberts, J.H. (2000). The intersection of modelling potential and practice. *International Journal of Research in Marketing* 17(2/3) 127-134.
- Schmittlein, D., D.G. Morrison, and R. Colombo (1987), "Counting Your Customers: Who Are They and What Will They do Next?" *Management Science*, 33 (January), 1-24.
- Silk, A.J. and G.L. Urban. (1978). Evaluation of New Packaged Goods: A Model and Measurement Methodology. *Journal of Marketing Research*, 15 (2), 171-191.
- Van Bruggen, G.H. and B. Wierenga (2010). *Marketing Decision Making and Decision Support: challenges and Perspectives for Successful Marketing Management Support Systems*. *Foundations and Trends in Marketing*, forthcoming.
- Van der Lans, R., G.H. van Bruggen, J. Eliashberg, and B. Wierenga (2010). "A Viral Branching Model for Predicting the Spread of Electronic Word-of-Mouth". *Marketing Science* 29(2), 348-365
- Wierenga, B. (1974). *An Investigation of Brand Choice Processes*. Rotterdam University Press, 261 pp.
- Wierenga, B. (2008). The Past, the Present, and the Future of Marketing Decision Models. In B. Wierenga (Ed) *Handbook of Marketing Decision Models*. New York: Springer, 3-20.
- Wierenga, B., G.H van Bruggen. (1997). The Integration of Marketing Problem-Solving Modes and Marketing Management Support Systems. *Journal of Marketing* 61(3) 21.
- Wierenga, B. and G.H. Van Bruggen. (2000). *Marketing Management Support Systems: Principles, Tools, and Implementation*. Kluwer Academic Publishers, Boston, MA.
- Wierenga, B., G.H van Bruggen, R. Staelin. (1999). The Success of Marketing Management Support Systems. *Marketing Science* 18(3) 196-207.
- Wierenga, B., G.H. van Bruggen, and N.A.P. Althuizen (2008). "Advances in Marketing Management Support Systems". In B. Wierenga (Ed) *Handbook of Marketing Decision Models*, New York: Springer, 561-592.

