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Journal of Retailing 86 (1, 2010) 94–105

Journal of Retailing

Retail Shelf Allocation: A Comparative Analysis of Heuristic and Meta-Heuristic Approaches

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Abstract

This research presents a retail shelf-space decision model that incorporates a nonlinear profit function, vertical and horizontal location effects, and product cross-elasticity. We propose a linear programming formulation of the nonlinear profit function that can solve the shelf-space problem optimally. We describe potential advances in heuristic and meta-heuristic algorithms and compare the approaches through simulations and a field experiment. We discuss the impact of the number of item facings, vertical location, and horizontal location (e.g., we find the vertical location effect is approximately double the size of the horizontal location effect on profit performance).

Keywords: Retail shelf space; Meta heuristic; Nonlinear profit function

Retail shelf-space management is one of the most difficult aspects of retailing. A significant reason is that while retail shelf-space is fixed, the numbers of new potential products (Dreze, Hoch & Purk 1994), customer wants (Corstjens & Doyle 1983), and competitors (Grewal et al. 1999; Hansen 2009) are constantly growing and evolving. At the same time, customers are consolidating shopping trips toward multi-purpose shopping (e.g., Popkowski et al. 2004). Thus, the success of any retailer depends on its ability to match its changing environment by continually deciding between *how much* of *which* products to shelve *where* and *when*. Indeed, the shelf *location* of products can significantly affect the products, and thus merchandise category, performance (Dreze, Hoch & Purk 1994). Thus, retailers benefit by expanding their focus from product-level performance to the total shelf-space configuration.

The practice of analyzing shelf-space costs and product performance has been standard for several decades in retail practice and literature (e.g., Wickern 1966); many retailers have now adopted software programs such as Spaceman or Prospace for creating planograms. These programs can display historical product sales, profits, or inventory turnover information. In past years, the actual decisions of items to shelf location were usually made through human judgment because of the near infinitesimal combinations of shelf-space arrangements. As a result, shelf-space software programs are often only used as a visual template, and not to perform analysis. However, advancements in computing resources have permitted the development of more complex shelf-space models that are more consistent with consumer decision making (e.g., Borin & Farris 1995; Urban 1998).[3] Retail corporate buyers, category managers (who are employed by manufacturers), and retailer consultants can use these shelf-space models to improve their decision making, resulting in better financial performance.

In this research, we first integrate the following three important elements into the basic shelf-space decision model: (1) a nonlinear profit function, (2) location effects, and (3) product cross-elasticity. In contrast to much of the research that has used *nonlinear programming* to model the nonlinear profit function, we propose a novel *linear programming* formulation of the nonlinear profit function that can solve the shelf-space problem

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[3] We recommend readers interested in early shelf space model evolution literature to Anderson and Amato (1974), Hansen and Heinsbroek (1979), Corstjens and Doyle (1981), Gochet and Smeers (1979), and Bultez and Naert (1988).

0022-4359/$ – see front matter © 2010 Published by Elsevier Inc on behalf of New York University.
doi:10.1016/j.jretai.2010.01.004

optimally. We then extend the retail shelf-space literature by comparing potential advances in heuristic and meta-heuristic algorithms of the shelf-space model. We compare the different approaches/extensions through simulations and a field experiment. Unlike prior experiments that look at one store using a before-after scenario (i.e., lacking a control group), we investigate differences *between* three different configurations (i.e., including a control group) using a before-after comparison. Thus, we can control for both natural growth in consumer populations (in the control group) as well as change due to the novelty of making any changes at all (by having two different change groups of stores). The results indicate that the meta-heuristic approach outperforms the heuristic approach (and is closest to the linear programming formulation) in the simulations and the heuristic and control group in the natural field experiment. In summary, we find that the number of facings, vertical location, and horizontal location each have a significant, near-equivalent impact. We conclude with a discussion of limitations and implications.

The shelf-space allocation model

To develop a basic understanding of how heuristic and meta-heuristic models can aid retailers, we first describe the basic shelf-space management problem as follows:

$$\text{Maximize} \sum_{j=1}^{N} \sum_{k=1}^{S} P_{jk} * x_{jk} \tag{1}$$

In essence, the formula multiplies the profit of an item (P_{jk}) by the number of facings of that item (x_{jk}). We use the term "item" throughout this paper to refer to an individual product stock keeping unit (SKU). Although many products may have one facing on a shelf, at times other products have multiple facings. It is assumed that increasing the facings of an item normally has a positive effect on the item's sales, as found in the literature (e.g., Baker and Urban 1988; Urban 1998, 2002, 2005). Otherwise, the number of facings would be kept to one per item, thus allowing room for additional items on the shelf.[4] The formula repeats the process for each product (j) on each shelf (k) to calculate the total profit across all products (N) on all shelves (S). The manager's goal becomes finding the right combinations of items and facing across the shelf-space to maximize total profit. Following Yang and Chen (1999), the problem is presented here as an integer programming formulation because retailers are interested in solutions that give integers, or whole numbers, of suggested product facings.

[4] Retail practice provides prima facie evidence of this assumption about the incremental value of multiple facings. We urge the reader to observe any aisle of a retailer. The reader will witness several products with multiple facings. We ask: As retailers have more products available to them from manufacturers than actual shelf space permit, *why* would retailers choose for any product to ever receive more than one facing? The only logical reason is if, on average, the *additional* space allocated to the product results in more sales or profit than if the next best non-displayed product was included.

Accounting for the nonlinear profit function

A nonlinear profit function is one approach that retailers can use to make better shelf-space arrangement decisions (see, e.g., Lim, Rodrigues & Zhang 2004). To demonstrate this function, we examine the basic retail shelf model shown in Eq. (1). The total profit generated by a particular product in that equation is equal to the per unit product profit dollars multiplied by the number of shelf facings. However, while a retailer might double the sales of an item by giving it two facings on the shelf, the sales or profit increase from two to three facings is usually less than the increase from one to two facings. Likewise, the increase from three to four facings will be even less, and so forth. That is, there is a nonlinear relationship between the number of facings and the profit dollars produced—referred to as a nonlinear profit function.

We emphasize that the term "nonlinear profit function" is not equivalent to—nor does it necessarily imply—"nonlinear programming." Indeed, nonlinear formulations of shelf-space problems with nonlinear profits in the literature are unable to find optimal solutions for the majority of shelf-space problems (e.g., Lim, Rodrigues & Zhang 2004). Consistent with Hansen, Raut and Swami (2006), we propose that retailers can use a "linear integer programming formulation" of the "nonlinear profit function" in the shelf-space model.[5] As such, the linear model retains the advantages of the diminishing returns that accrue with additional space for any given product. In summary, as shown in Appendix A, a nonlinear profit function can be modeled using linear programming.

Accounting for the horizontal directional effect

Including directional effects in the shelf-space model is another approach that retailers can use to make better shelf-space arrangement decisions. The general concept of "location" affects many aspects of retailing, from the store location to departmental adjacencies to category and subcategory shelf-space arrangements. Research on the general topic of location goes back to concepts such as Reilly's (1929) gravitational models. Specifically, in reference to the shelf-space configurations, the location of a product can significantly affect its profit generation (see, e.g., Dreze, Hoch & Purk 1994). For example, most retailers intuitively expect cold cereal products placed at or above the shopping cart level generate more sales and profit than if the same products were placed on the bottom shelf. Additionally, people might read shelf tags (habitually) from left to right within a given section of shelf (i.e., a horizontal effect). Products closer to the end of the aisle might experience more passing traffic than items located toward the center of the shelf, and thus have increased sales due to their proximity toward the end of the aisle.

[5] Nonlinear models can be transformed to linear models by a conversion. For example, consider the nonlinear objective function: max ($x_1 * x_2$), where x_1 and x_2 are binary variables (e.g., Corstjens & Doyle 1983). This nonlinear function can be transformed into a linear function as follows: max z, where $z \leq x_1$; $z \leq x_2$ (so that all the terms are linear).