SIMULATING THE ASSORTING PLANNING PROCESS TO SUPPORT THE DECISION-MAKING OF GROCERY WHOLESALERS: THE MEXICAN MARKET CASE.

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ABSTRACT

Having the best assortment in a retail store is a complex task for the category manager in which their main job is to maximize the overall performance of each of the products cataloged, maintaining a balance between suppliers, the company and customers. The accommodations made on the shelf are made by assortment planning models in which only a single category is used to carry out this choice. However, they are overwhelmed when they have to evaluate between categories, such as complementary products. It has developed assortment planning model with dynamic programming in which based on Monte Carlo simulation using @RISK software to support the decision-making of a Mexican grocery wholesaler. Our simulation results demonstrate that increasing the scope of faces to analyze, we can give the decision maker a better picture of the assortment the store should display.

Keywords: Dynamic programming, Assortment planning, Montecarlo simulation, Retailing

1. INTRODUCTION

Nowadays, grocery wholesale in Mexico trade finds its development conditioned by a range of pressures; customers increasingly orient their preferences looking forward greater value propositions. Among the proposals, the price is a fundamental component in the evaluation of a proposed retail, the comfort in terms of proximity, quality and variety of the products, customer service, and categories selected, as well as offering services that might result in saving time.

On average we buy the same 150 products, which represent 85% of the needs at home. (Schneider & Julie, 2011) The rest are new products, where only 3% out of the other 15% missing are products that exceed sales in more than 50 million dollars. One of the great challenges trade faces is on choosing which products to exhibit, since you often ask yourself, which product do I take away in order to exhibit the new one?

How we assign products in a finite and limited space on shelves is a critical operational decision that all retailers face. This decision is directly related to the profitability of the organization as it affects operating costs and revenues. It affects costs in the list of products we have, including transportation, purchase orders, inventory maintenance, reshuffling the product, and the possibility of falling into unavailable status because of not having quantity demanded by customers.

Businesses need to meet this consumer demand by balancing the installed capacity (furniture, shelf) depending on the variety of choices (product number) and service levels on the shelf (number of units of a product) . As a central result of strategic decisions the trader should take into consideration four important aspects:

- *Listing*: Size range. What products do I select in order to satisfy customer demands?
- *Facing*: Management of space on the shelf. Is the space finite on a shelf, could it be increased? Should we remove products? How many fronts do I give to each product?
- *Replenishing*: The refill. How logistics is generated to restock the product?
- *Pricing*: The price. what price should the product selected have?

Offering a wider range can generate that appropriate service levels might not occur, and vice versa, as well as the shelf space is limited. Traders and manufacturers try to meet consumers' satisfaction with the right merchandise in the right store at the right time. (Hübner, 2011).

This task is carried out by the category manager. *Category management* is a merchandising technique that some firms – including several supermarkets, drugstores, hardware stores and general merchandise retailers – use to improve productivity. It is a way to manage a retail business that focuses on the performance of product category results rather than individual brands. It arranges product groupings into strategic business units to better meet consumer needs and to achieve sales and profit goals. Retail managers make merchandising decisions that maximize the total return of the assets assigned to them. (Bhatia, 2008). In other words, category management is a way of organizing retail product management so that suppliers, central operations and outlet level activities are integrated into the process, in which is geared to responding effectively to consumer demand.

The category management analysis focused on the use of assets (inventories, surface and eventually employees) and results (margin) allow you to focus categories as strategic business units. Knowing the behavior of each product per store provides a more accurate building plans for each category, on which the chain suppliers and agree to coordinate their efforts basis. The margin analysis versus sales volume will allow distinguishing products according to their contribution within the category. We are not interested only on those who leave higher margin, but also those that sell well.

Retailers typically solve decision problems sequentially: determining the assortment, allocating it to the shelf and finally determining order sizes. However, there are products and categories that only have to sell if there is another who complements, for example, milk, in a study conducted in the UK it was found that only 12% of consumption is done alone, consumption is accompanied generally. (Centre for European Agricultural Studies & Institute for the Management of Dairy Companies, 1999) Therefore, when performing assortments that are carried out not fail to see the chain of influence they have and how they can benefit the store sale.

The objective of the category manager is to organize on a wiser way product assortment as well as the marketing plans to generate better profit contribution of limited display space, especially with the increase of new products.

The category manager must handle the assortment of the categories of the stores according to the following diagram:

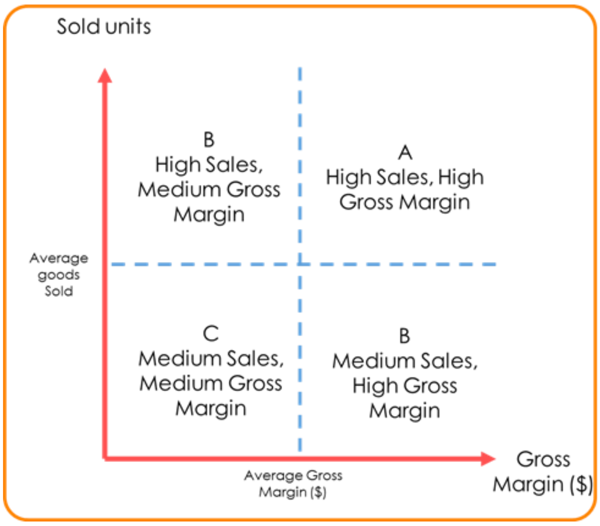

Figure 1Classifying SKUs (Stock Keeping Units) of scorecard categories.

In Figure 1according to (Ring & Tigert, 2002) we find that most of the catalog of a category is in the C sector, recent business deteriorates very significantly, though subtle. A low contribution they add a cost of maintaining inventories, but above all, tie up capital or bargaining power with suppliers. This bargaining power could very well apply to products that contribute faster, allowing greater capital turnover, rather than in a low margin business is extremely significant. Most of the complementary products within this category are the first products to withdrawal the assortment the retail has to offer.

A key to achieving the desired performance in the arrangement of the shelf appearance depends on the category manager having access to an efficient decision-making system that allows managing the physical space. Traditional tool for managing space in stores is the planogram. However, software applications available on the market made the arrangement of the product by simple rules of thumb for allocation based on sales of their products.

Among the existing models in literature regarding managing shelf space, one of the first studies was done by (Hansen & Heinsbroek, 1979). In his model, the demand for each product is a function of the elasticity of space. Its model seeks forward maximizing profits for retailers liable to a limit of available space on the upper and lower quantity of each product limits, as well as in the whole of the useful fronts values. In addition, (Zufryden, 1986) presented a dynamic programming formulation for a problem with the elasticity of space and marketing variables related to demand, including the price. The article written by (Yang & Chen, A study on shelf space allocation and management, 1999) assumed a linear utility derived from the fronts of the products. They formulate a problem of accommodation space with a horizontal and vertical effect of accommodation. (Yang, 2001) proposed a heuristic model of the backpack. He found an optimal solution only in very simple versions. (Lim, Rodriguez , & Zhang , 2004) based on Yangs' proposal, they work for a goal - heuristics. A hierarchical Bayes model is proposed by (van Nierop , Fork, & Franses , 2006) to estimate the interaction between the arrangement of the shelf , marketing activities and stochastic demand. They did it by working with simulated annealing. (Murray , CC ; Talukdar , D; Gosavi , A, 2010) worked together to create a decision making model based on which products must be accommodated as well as the price for each item by using MINLP - solver. (Hansen, Raut, & Swami 2010) investigated a goal decision model- heuristic with which the fronts of the products are proportional to the demand generated by them.

A dynamic programming approach is proposed to select optimally between a given set of products and allocate shelving units in the whole space for the selected products on the shelves of the Mexican cash and carry wholesaler. The approach is designed to take into consideration the general shelf specifications such as the size, as well as revenues from the sale of such products.

Before going into details contained in the article, a model for the optimization and simulating parameters scenarios is described in section 2. The results of simulation are shown in section 3, and finally, in section 4 the contribution and conclusions of it are presented.

2. THE MODEL FORMULATION

We now turn to a discussion of the optimization model components and its formulation as a mathematical program. Model is based on the knapsack model, since it looks forward exhibiting products in quantity and in a way in which we can maximize revenue. The knapsack problem is a classic problem of linear integer programming.

Maximize

$$z = \sum_{i=1}^{n} p_i \, x_{ij} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Subject to.

$$\sum_{i=1}^{m} w_i \, x_{ij} \leq W_j \qquad j = 1, \ldots, m \qquad \ldots. (2)$$

$$x_{ij} \geq 0 \qquad i = 1, 2, \ldots, n$$
$$\text{And integer} \qquad j = 1, \ldots, m \qquad \ldots (3)$$

Where p_i the profit earns by each SKU i ($i = 1, 2, \ldots, n$), w_i the space required in centimeters by each SKU i and W_j the total length available at the shelf are integers. Where $j = 1, \ldots, m$ is the store selected. In other words, suppose you have to fill a shelf with different SKU with a revenue p_i and distance in w_i without exceeding total space given W. The problem is to find the maximum feasible allocation of items for the total value of the products on the shelf. Each item that can fit on the shelf has a size and an associated benefit. The shelf has a limited capacity.

2.1. Dynamic Programming Formulation

Dynamic programming appears to provide an effective technique to provide solution that solves the problems of accommodation in the shelf space. (Flores de la Mota, 2015) Among its advantages, we have, that it can easily handle variables for exchange, for example changing branch database to verify the maximum space you have to display products, and the best of all, is that you can handle integer solutions, you cannot divide a product in tenths of a party, in enters completely or does not enter in the shelf.

First, we consider the general problem of N items. If kj is the number of units of an item i , the problem becomes:

Maximize

$$v1k1 + v2k2 + \cdots + vNkN \qquad (4)$$

Subject to

$w1k1 + w2k2 + \cdots + wNkN$ less than or equal to W
$k1$ integer not negative (5)

The dynamic programming model is constructed considering the following three basic elements:

1. Stage j is represented by i tem $j, j = 1,2, \ldots, N$
2. State y_j, in the stage j, is the total space assigned to stage j, $j+1, \ldots, N$; $y_1 = W$ y $y_j = 0,1, \ldots, W$ para $j = 2,3, \ldots, N$.
3. Alternativek_j, in stage j, is the number of unit of each item j. The value of k_j, could be as little as zero, or as big as $[W/w_i]$, where this ratio is the smallest integer maximum obtained from $[W/w_i]$.

The stages represent the items, then, we have three steps $j = 1,2, \ldots N$. The state of step j, represents the total space of the j items, plus all the items that will be accommodated later on the shelf. The decision in step j is: ¿How many products j must be accommodated in that shelf? The answer is kj.
Then you have the following recursive formulas:

Is $\mathrm{f_i(y_i)}$ = optimal value of stages j, j + 1, … , N given the state $\mathrm{y_j}$.

Recursive equations call are:

$$f_N(y_N) = \max_{\substack{kn=0,1,\ldots,|yN/wN| \\ yN=0,1,\ldots,W}} \{v_N k_N\} \qquad (7)$$

$$f_j(y_j) = \max_{\substack{kj=0,1,\ldots,\left|\frac{yj}{wj}\right| \\ yj=0,1,\ldots,W}} \{v_j k_j + f_{j+1}(y_j - w_j k_j)\} \qquad (8)$$

2.2 Montecarlo Simulation

Figure 2 Selected refrigerator in which the maximum distance is 235 centimeters.

In this context, Monte Carlo simulation could be considered as a methodical way to perform the what-if analysis, where we seek how it might behave if w_i=1, 2, 5 maximum fronts, how many different items we would have, and how items of classification A, B and C will behave.

Previous data would be our output variables. And as random input variables, have been based on demand information provided by the wholesaler for choosing the best choice for the main refrigerator with $W = 235\ cm$ in which selection within the 179 cataloged products in which w_i of each item in centimeters is known, given the average standard deviation of demand and sales of the last 12 months in which they behave on a normal way. To run the simulation @RISK software was used for performing the study.

3. RESULTS

The simulation model range has been used to understand the behavior of few different items could have our exhibit, and understand how our profitability would be affected with the choice given of 1000 range iterations.

Table 1Risk Output Report for $W = 235$ & maximum faces by SKU = 1

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$135,267	$165,275	$197,410	$149,085	$181,549	$0
Total of SKU faced		13	14.364	20	13	16	0
Total of SKU "A" faced		7	9.504	14	8	11	0
Total of SKU "B" faced		1	4.073	7	3	6	0
Total of SKU "C" faced		0	0.787	2	0	1	0

Table 2Risk Output Report for $W = 235$ & maximum faces by SKU = 1

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$186,931	$236,343	$286,353	$206,585	$265,885	$0
Total of SKU faced		7	8.6	15	7	12	0
Total of SKU "A" faced		5	6.907	10	6	9	0
Total of SKU "B" faced		0	1.557	7	0	3	0
Total of SKU "C" faced		0	0.136	2	0	1	0

Table 3Risk Output Report for $W = 235$ & maximum faces by SKU = 2

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$232,177	$316,700	$410,037	$266,018	$371,217	$0
Total of SKU faced		3	3.124	8	3	4	0
Total of SKU "A" faced		2	3.103	7	3	4	0
Total of SKU "B" faced		0	0.021	2	0	0	0
Total of SKU "C" faced		0	0	0	0	0	0

The results obtained using the simulation model range in @RISK allows us to see that, the greater the range of products, the utility may be less when having at least one front displayed, as in Table 1 in which an average of 14 SKU exhibited, we are located in the middle of the presumable utility buildable in which at least we would have nine SKUs "A" , 3 SKU "B " and at least 1 SKU " C " displayed, and a grater utility when we have 5 possible fronts of articles, as in Table 3 in which in average 3 SKU displayed are located in the middle of probable utility buildable in which at least we would have three SKU "a" , at least 1 SKU "B " and already It not is necessary to display a SKU " C ".

3.1. Validation

It has been carried out the validation of the simulation performed taking into account the latest sales period registered to learn how has deviated from the average in which it was found that:

Table 4Risk Output Report for $W = 235$ & maximum faces by SKU = 1 with a fixed Demand

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$137,405	$165,201	$194,827	$149,535	$180,321	$0
Total of SKU faced		13	14.319	21	13	16	0
Total of SKU "A" faced		6	9.486	14	8	11	0
Total of SKU "B" faced		0	4.053	8	2	6	0
Total of SKU "C" faced		0	0.78	2	0	1	0

Table 5Risk Output Report for $W = 235$ & maximum faces by SKU = 1 with a fixed Demand

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$187,704	$236,075	$302,852	$205,560	$263,878	$0
Total of SKU faced		7	8.587	24	7	12	0
Total of SKU "A" faced		5	6.903	16	6	9	0
Total of SKU "B" faced		0	1.566	7	0	3	0
Total of SKU "C" faced		0	0.118	2	0	1	0

Table 6Risk Output Report for $W = 235$ & maximum faces by SKU = 2 with a fixed Demand

Name	Graphic	Min	Mean	Máx	5%	95%	Err
Profit-earning capacity		$228,338	$316,460	$446,847	$265,619	$371,299	$0
Total of SKU faced		3	3.111	7	3	4	0
Total of SKU "A" faced		2	3.099	6	3	4	0
Total of SKU "B" faced		0	0.012	1	0	0	0
Total of SKU "C" faced		0	0	0	0	0	0

3.1.1

Table 7Err between Table 1 and Table 4

Name	% Diff Min	% Diff Mean	% Diff Máx	% Diff 0.05	% Diff 0.95	% Diff Err
Profit-earning capacity	1.56%	-0.04%	-1.33%	0.30%	-0.68%	-
Total of SKU faced	0.00%	-0.31%	4.76%	0.00%	0.00%	-
Total of SKU "A" faced	-16.67%	-0.19%	0.00%	0.00%	0.00%	-
Total of SKU "B" faced	-	-0.49%	12.50%	-50.00%	0.00%	-
Total of SKU "C" faced	-	-0.90%	0.00%	-	0.00%	-

Table 8Err between Table 2 and Table 5

Name	% Diff Mín	% Diff Mean	% Diff Máx	% Diff 0.05	% Diff 0.95	% Diff Err
Profit-earning capacity	0.41%	-0.11%	5.45%	-0.50%	-0.76%	-
Total of SKU faced	0.00%	-0.15%	37.50%	0.00%	0.00%	-
Total of SKU "A" faced	0.00%	-0.06%	37.50%	0.00%	0.00%	-
Total of SKU "B" faced	-	0.57%	0.00%	-	0.00%	-
Total of SKU "C" faced	-	-15.25%	0.00%	-	0.00%	-

Table 9Err between Table 3 and Table 6

Name	% Diff Mín	% Diff Mean	% Diff Máx	% Diff 0.05	% Diff 0.95	% Diff Err
Profit-earning capacity	-1.68%	-0.08%	8.24%	-0.15%	0.02%	-
Total of SKU faced	0.00%	-0.42%	-14.29%	0.00%	0.00%	-
Total of SKU "A" faced	0.00%	-0.13%	-16.67%	0.00%	0.00%	-
Total of SKU "B" faced	-	-75.00%	-100.00%	-	-	-
Total of SKU "C" faced	-	-	-	-	-	-

This has already generated an important aspect in which if we reduce the catalog it could be beneficial to the wholesaler because having lower catalog, management is easier to handle, however, for customers is not necessarily the best. Among the leading causes in which a consumer goes to the point of sale, would be the catalog that the wholesaler can offer.

	w = 1	w = 2	w = 5
% of SKU "A" faced	66%	80%	99%
% of SKU "B" faced	28%	18%	1%
% of SKU "C" faced	5%	2%	0%

Table 10Percentage of SKU faced by the 3 different scenarios

This work allows the wholesaler to recognize how to balance its SKU catalog, in which if it exhibits just one front for each item, distribution tends to seem like a Pareto distribution where with the 66% of the items “A”, we will be able to accommodate them maximizing out profitability with the assortment given.

4. CONCLUSIONS AND FUTURE WORK

Category management is among the biggest challenges that a commercial chain might have, in which we depend on the strategic decision of the company to choose the best assortment for each store or branch. Often, as in the case studied, we have about 180 SKU available for displaying. We have that amount of products because every area that participates in the chain has their own tastes, but thanks to the study presented, we can realize we should maintain assorting open since, as it was mentioned in the introduction, we should take into consideration the assortment to offer, the service level we have, as well as the resupply (replenishment) and the prices we have to maximize profitability.

Dynamic programming models allow them to be flexible in placing restrictions on future work that would be necessary to try different industries to the one studied in this work as the fashion industry.

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