Store-Wide Space Planning at Mini Mall

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***Abstract*— We propose to maximize the overall profits of Mini Mall, a supermarket in Nabatieh, by promoting impulse buying. To do this, we aim to optimize shelf-space allocation of supermarket products in a way that increases the visibility of items with a high impulse purchase rate and thus drive the customers to buy more. Following the analysis of 51,379 e-receipts, the various products (i.e. Twix, Persil, etc.) were organized into product categories and located on the current layout of the supermarket. Depending on the location of the shelves within the store, product visibility rates and customer traffic intensity rates may fluctuate, which is why calculating those rates was necessary. We also conducted surveys to compute the impulse purchase rates of specific product categories. The results of these three computed rates were used to clearly demonstrate which areas of Mini Mall attract the most customers. Visualizations of correlations in the customer basket data gathered using R software were developed to better picture the information presented. Based on our analysis, we propose optimal positioning of products around the store, and we forecast a significant increase in profitability based on these moves. While it is not possible to "manually" figure out the best revenue-boosting moves, we suggest a 0-1 integer programming model towards this end. The model formulation and the estimation of its input parameters are complete. Our ongoing work is on coding and solving the model as well as using AMPL compiler and CPLEX solver which can handle a model with thousands of decision variables and constraints such as ours. Our work is expected to be a successful application of predictive and prescriptive based on big data in retailing.**

***Keywords*—Impulse purchase rate, product visibility, traffic intensity, 0-1 integer programming model, R, AMPL, CPLEX.**

I. Introduction

We live in a globalized world where competition is at its highest; therefore, any company that wants to survive in this environment is bound to seek a competitive advantage. Looking closer at the country we live in and understanding our responsibility towards building a better community, we pursued a project that could empower a supermarket's profitability at zero costs. According to Nielsen statistics [1], the FMCG market size in supermarkets in Lebanon is $943 million and has seen a 3% drop in revenue between 2018 and 2019. This will be translated into layoffs if nothing is done to keep this struggling sector on its feet. Mini Mall, a three-story supermarket with a total area of 1,000 m^2 located in Zibdine (Nabatieh), is an example of a supermarket that observed a recent drop in revenues. As industrial engineering students, we know that our major covers many disciplines that could help in that field, including the optimization of system processes with the end goal of enhancing performance and gaining a competitive advantage, which is why we contacted Mini Mall and offered our help. The supermarket is owned by Mr. Hussein Ayoub, who is also our person of contact for the project.

We, as industrial engineers, will try to use knowledge acquired throughout our four-year program at AUB to maximize Mini Mall's gross profits through promoting impulse buying. This strategy is very important, particularly after the recent economic events that significantly decreased people's purchasing power. As a result of these events, people are now tending to stick as much as possible to pre-set shopping lists which are carefully considered prior to going on their "shopping trips". Supermarkets are now struggling to attract customers to buy lucrative products which genuinely constitute more than 50% of their profits [2], since these products have high marginal profits in contrast to products like bread, water, cheese and eggs which have relatively low marginal profits.

II. Objectives

Accordingly, our aim in this project is to stimulate impulse buying from customers with the purpose of increasing Mini Mall's overall profits and giving the supermarket a significant competitive advantage against the numerous competitors who are competing to gain market shares and profits in a downsizing economy. We intend to increase profits through optimizing store-wide shelf-space allocation using the following hierarchy of decisions:

i. Group items into product categories and product groups according to similar characteristics
ii. Locate the product categories within the shelves (e.g. middle of shelf or at the end of the shelf)
iii. Analyze Mini Mall's e-receipts and profit margins
iv. Calculate traffic intensities, visibility rates and impulse purchase rates
v. Create visualizations of the correlation in the data
vi. Solve the 0-1 integer programming model

III. Background and Literature Review

In this section, we present background and literature related to our space planning problem. Specifically, we give a background on the importance of impulse buying and the effect of shelf space display on impulse buying.

A. Impulse purchasing and exposure

An impulse purchase, in the context of a supermarket, is defined as an unplanned decision to buy a specific product [3]. A study conducted by Popai and Du Pont concludes that "approximately 65% of all supermarket purchase decisions were made in-store with over 50% of these being unplanned"

[4]. Promoting impulse purchases can therefore lead to an increase in profits. Customers experience this urge to purchase impulse items as a result of in-store stimuli that could depend on two factors: Exposure and consumer-commitment [5]. Our project relies primarily on exposure techniques, as our target is to attract consumers to buy more unplanned items by interchanging their locations on the numerous shelves.

B. *Shelf display allocation*

Studies completed in West Germany and in the UK have determined that sales of products are effectively influenced by the difference in display [6]. One explanation for this is that customers tend to pay more attention to products placed at eye-level. In one study, a group of researchers [7] studied the profit generated by interchanging low penetration toothbrushes (bought every 4-6 months) and high penetration toothpaste (2 months), whereby toothbrushes were now more visible; the result was toothbrushes experienced an 8% increase in sales while toothpaste wasn't affected, hence confirming the theory. The researchers in [7] interchanged two sub-category products according to penetration level; we will be interchanging product categories according to impulse rates. To have an idea of how locations affect the visibility of a product, these same researchers measured the coordinates of the products on the shelves and integrated the coordinates into a model using a polynomial function [7]. In our case, we considered a particular product to be part of a bigger product category, and therefore we are not measuring the position of single products but rather the position of the entire product categories. The measures and their visibility were calculated manually, unlike the above-mentioned example which used a function.

C. *Surveys and rates*

In another article, researchers examine how products that give a more intense positive affect, such as chocolate bars, have a higher probability of being purchased than products that are less associated with pleasure (e.g. fruits) [8]. Surveys must be carried out to determine the impulse purchase rate of the items being sold. Kollat and Willett's surveys consisted of face-to-face interviews with customers at the entrance of the supermarket to comprehend the buying intentions, and then after the purchase to write down the unplanned purchased items [9]. Our method is slightly different due to lack of time and resources at hand: our surveys are based on face-to-face interviews after the purchase and consists of a simple question: "What items on your shopping list have you purchased that you did not plan to buy?". The results of the surveys helped us calculate impulse purchase rates consistent with Mini Mall's clients' behaviors.

D. *Shelf space optimization method*

In their works, Ke and Van Ryzin used heuristics to solve shelf space allocation problems [10]. In our work we will be using optimization techniques; however, we will be using heuristics in order to validate our model during the first part of our final year project by manually changing product shelf-allocations according to industry traditions (such as putting fresh items at a higher floor)m and prove that this model will lead to an increase in profit. Researchers in [11] focused on constructing the objective function (maximize: $\sum p_m i_p n_e$) which refers to the profit from impulse purchases; in our paper we will be focusing on constructing this objective function on AMPL to solve it and find the optimal allocation of product groups [11].

IV. METHODS

A. *Notation and Formulation*

As discussed previously, our main objective is to increase profits through promoting impulse buying by optimizing shelf-space allocation through the following set of decisions:

- Finding the optimal shelves for each of the products' groups (which consist of categories) in each of the three floors of the supermarket.
- Assigning the product categories to the optimal positions within the shelf chosen.
- Deciding on the optimal space that should be allocated to each product category on its shelf.

In order to solve this optimization problem, we will employ the model of optimization implemented in [11]

Consider the following notation:

1) Sets:

- A: Set of aisles.x
- S: Set of shelves.
- SS_a: Set of shelves located in same aisle a; for all a ∈ A.
- $E_s \equiv \{\alpha_s \dots \beta_s\}$: Set of edges (shelf segments) associated with shelf s, for all s ∈ S.
- $E \equiv \cup_{s \in S} E_s$: Set of all walkway edges numbered consecutively from 1 to E.
- P: Set of all product categories.
- O: Set of product pairs (p, p′) ∈ P that should not be allocated to the same shelf because of lack of affinity (e.g. cleaning items and bread).

2) Input Parameters:

- se: Shelf space available along the edge of a shelf segment e, for all e ∈ E.
- $te \in [0,1]$: Customer traffic density along edge e, for all e belong E.
- lp, up: The lower and upper bounds for the space required for each product category p or all $p \in P$.
- $ip \in [0,1]$: Impulse purchase rate for product category p.
- pm: Profit margin for the product categories; all $p \in P$.

3) Decision Variables:

- $w_{ps} \in \{0,1\}$: $w_{ps}=1$ if the product category p was allocated to shelf s; for all $p \in P$, $s \in S$.
- $q_{pe} \in \{0,1\}$: $w_{pe}=1$ if the product category p was allocated to edge e; for all $p \in P$, $e \in E$.
- s_{pe}: Shelf space given to product category p along the edge e of a give shelf space, for all $p \in P$, $e \in E$.
- n_{pe}: The probability that a certain product category which is located on an edge e of a shelf s will be noticed by a customer when he passes by. $$n_{pe} = (t_e \times s_{pe})/s_e \quad (1)$$
- n_e: total noticeability of each product category p for all $p \in P$ $$n_e = \sum\sum n_{pe} \ \forall s \in S \quad (2)$$

4) Optimization Model

Maximize $\sum_{p\in P} p_m i_p n_e$ (3)

Subject to:

$n_{pe} = (t_e \times s_{pe})/s_e \ \forall\, p\in P,\, s\in S,\, e\in E$ (4)

$n_e = \sum_{s\in S}\sum_{e\in Es} n_{pe} \ \forall\, p\in P$ (5)

$\sum_{s\in S} w_{ps} = 1 \ \forall\, s\in S,\, \forall\, p\in P$ (6)

$l_p < \sum_{s\in S}\sum_{e\in Es} s_{pe} < u_p \ \forall p\in P$ (7)

$\sum_{p\in P} s_{pe} < s_e \quad \forall s\in S$ and $e\in E_s$ (8)

$q_{pe} < w_{ps} \ \forall\, p\in P,\, s\in S,\, e\in E$ (9)

$\sum_{e\in Es} q_{pe} > w_{ps} \ \forall\, p\in P,\, s\in S$ (10)

$w_{ps} + w_{p's} < 1 \ \forall\, (p,p')\in O,\, s\in S$ (11)

$w_{ps} - w_{p's} = 0 \ \forall\, (p,p')\in W_1,\, s\in S$ (12)

$\sum_{s\in SSa} w_{ps} - \sum_{s\in SSa} w_{p's} = 0 \quad \forall\, (p,p')\in W_2,\, a\in A$ (13)

w,q binary, $s>0$, $0 < n < 1$ (14)

In brief, equation (3) represents the objective function that maximizes the impulse buying profit. Constraint (4) represents the visibility of a product category. Constraint (5) is a metric that captures the total visibility of a product category. Constraint (6) restricts each product category to a single shelf. Constraint (7) ensures that the total shelf space allocated to a product category lies between its minimum and maximum space requirements. Constraint (8) requires the shelf space along any edge not to exceed its capacity. Constraint (9) ensures that a product cannot be assigned to an edge unless it is allocated to its associated shelf. Constraint (10) confirms any product group that is assigned to a shelf is also assigned to at least one of its edges. Constraint (11) forbids pairs of product categories having a lack of affinity from being assigned to the same shelf. Constraints (12)–(13) require product pairs having high affinity to be assigned to the same shelf and the same aisle, respectively.

B. Data Collection

First of all, Mr. Ayoub provided us with a layout of the three floors. Our first step was to locate the various products on the layout. Mini Mall supermarket currently has a portfolio of 66 product categories, which we also divided into 21 groups according to similar characteristics (as presented in Table I). The supermarket holds 43 shelves. After manually measuring the shelf-space occupied by each of the product categories, we used AutoCAD to create a detailed layout of the supermarket. We observed that a big portion of the Ground Floor is assigned to fresh product categories such as Deli Cheese, Meat and Chicken (#24, #26 and #27) as well as Chilled Fish (#29).

TABLE I. SAMPLE OF 4 PRODUCT GROUPS

	Product Groups	Product Categories
1	Paper and Packaging	Paper Goods & Toiletries (10), Trash bags (11), Food Bugs & Foil (12)
2	Bread	Bread (25), Cakes & Croissant (39)
3	Pet Needs	Pet food (22), Pet Accessories (23)
4	Water	Water (58)

V. RESULTS

A. Data Analysis

Mr. Ayoub provided a total of 51,379 customers' e-receipts extending over a period of two months (October and November). Using excel pivot tables and R software, we were able to analyze the receipts. We created a table portraying each product category's calculated sales volumes and their corresponding profit margins (as presented in Table II). This analysis informed us on important details of Mini Mall's profitability. For instance, product categories with the highest sales volume, such as Crisps Snacks & Nuts (#35, appears in 30421 receipts) and Chocolate (#38, appears in 28492 receipts), can be categorized as fast movers' goods since they have high sales turnovers. Product categories with the largest profit margins such as Energy and protein drinks (#61, 70%) and Deli Meat (#26, 47%) could be used to increase profitability considerably.

TABLE II. SAMPLE SHOWING SALES VOLUME AND PROFIT %

	Product Category, p	Sales volume, SV_p	Profit %
35	Crisps snacks & nuts	30421	21
38	Chocolate	28492	16
61	Energy & protein drinks	1244	70

B. Data Visualization

Next, we constructed a heat map that provides an immediate visual summary of the data collected. Heat map values are a result of the product of three variables summarized in Table III: Impulse Purchase Rate i_p, Traffic intensity t_e and Visibility Rate n_e. The equations used to calculate these three variables are:

$$n_e = \frac{\textit{shelf space allocated to product category}}{\textit{Total distance of the shelf}} \tag{15}$$

$$i_p = \frac{\textit{Unplanned purchases of a product category}}{\text{total purchases of product category}} \tag{16}$$

$$t_e = \frac{1}{\textit{Minimum distance to shelf}} \tag{17}$$

TABLE III. SAMPLE OF INPUT FOR HEAT MAP

p	Product category	t_e	n_e	i_p	$t_e * n_e * i_p$
5	Ice cream	0.04480949	1	1	0.04480949
30	Cream	0.06420051	0.067632531	0.1	0.00043420
60	Malt drinks	0.05241337	0.282352941	0.9	0.01331916

The visibility rate, calculated according to equation (15) required us to manually measure the distances. For example, Cream (#30) has the lowest probability of being seen along the shelf it is placed on. To calculate the traffic intensity, which is the probability that the customers pass by the product category, we measured manually the minimal distance from the entrance to that category. For product categories on the first and second floor, this distance is equal to the sum of the horizontal and vertical (stairs) distances [12]. The traffic intensity (equation (17)) is just the reciprocal of this distance, which is a relative measure or normalization. In order to calculate the impulse purchase rates, we surveyed 108 customers. The surveys were conducted after the purchase and consisted of asking customers what items on their shopping lists they had bought that they did not plan to buy. After analyzing the answers, and using equation (16), we calculated the impulse purchase rates. Product categories with high impulse purchase rates include Ice cream (#5, i_p =1), Energy and Protein Drinks (#61, i_p =1), and Malt Drinks (#60, i_p =0.9). On the other side, Chilled Fish (#29) and Pet Food (#22) have impulse purchase rates of zero. It is important to note that the minimum maximum space allocated to a product category on a shelf, *lp* and *up*, are set at ±7.5% of the present space apportioned.

After obtaining the values of three variables needed, we were able to calculate the values for the Heat Map. The values were then divided into four ranges and colors based on increasing order: Very Low, Low, Medium, and High. The Heat Map is finally exhibited in Fig. 1 and the range-color key is at the bottom of the map.

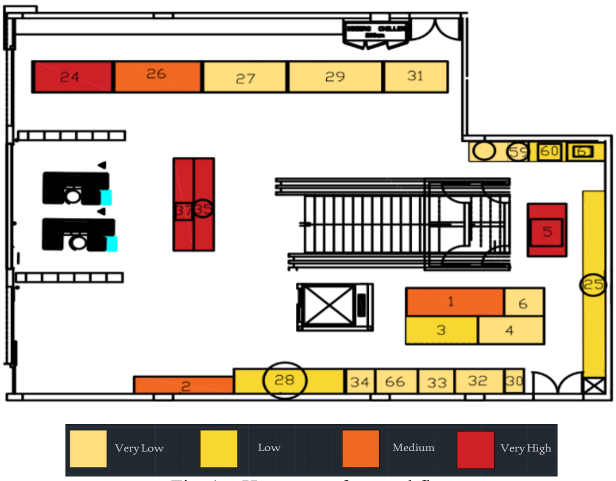

Fig. 1. Heat map of ground floor

For example, product categories colored in red correspond to 'High' range and means that this product category has a high probability of being bought, which are mainly located close to the entrance on the Ground Floor; with except of candies and sweet (#37), that are located on the first floor and still are marked in red because they have high visibility rate (1) and high impulse purchase rate (0.681). We observed that as you go higher in floors, product categories ranges proceed into Low or Very low: this is because they are further away from the entrance (smaller traffic intensity). One can also pinpoint Fast movers and Impulse categories: Fast movers are surrounded by squares on the map and represent the top ten product categories with the highest sales volume, and Impulse categories (10 product categories with the highest impulse rates) are surrounded by circles. We notice that fast movers are distributed randomly among the three floors, whereas most of impulse products are on the Ground Floor with none on the second floor.

In order to better understand the correlations that exist between different product categories, we created visualizations of our data. Fig. 2 exhibits the frequency of transactions along the y-axis and the basket size (or number of different product categories) along the x-axis. This figure can show if Mini Mall is ranging the correct assortment of products. In this case, for instance, around 7,000 transactions contain more than eight product categories, which means increased sales and profit. We can conclude from the figure that most of the transactions target only one product category (approximately 18,000 transactions)

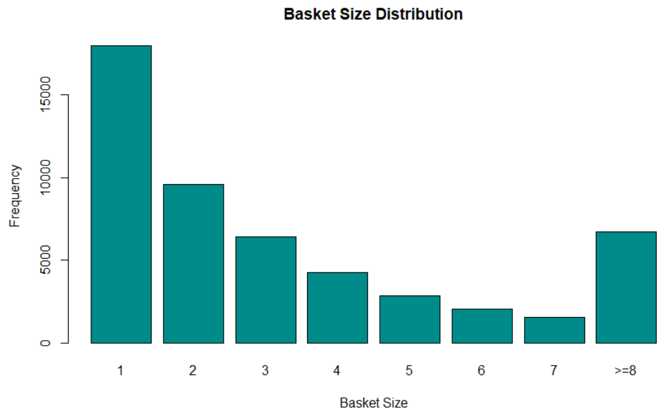

Fig. 2. Basket Size Analysis

For further investigation, we created a Heat matrix (Fig. 3) to visualize the frequency of two different product categories being bought together. Both rows and columns contain the 66 product categories but they are not shown for graphical constraints. In our case, local diary and bread have the highest correlation with a frequency of being bought together equal to 4983. This complies with the food culture in the area, where daily breakfasts include local dairy and bread. Biscuits and chocolates also have a high frequency of being bought together (4394 times).

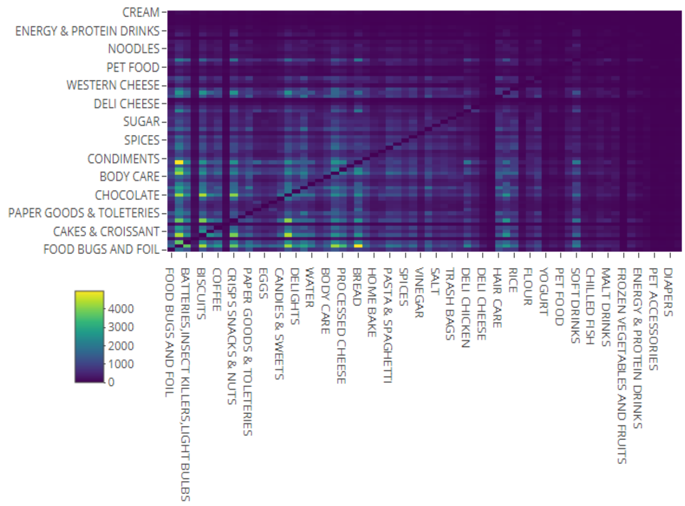

Fig. 3. Heat matrix showing dual relationship between product categories

We performed a Pareto analysis to test if 20% of the product categories occupy 80% of the sales volume. However, the results do not verify this principle. In fact, 20% of the 66 product categories (meaning 13 product categories) occupy 61.2 % of the quantity sold or quantity sales volume. The top three highest percentage of sales volume, based on console window in R, are: Crisps Snacks and Nuts (24%), Local Dairy (6.81%), and Chocolate (6.78%).

C. *Manual Changes*

To test that our objective is viable and that inter-changing product categories does really increase profit generated from impulse buying, we manually exchanged locations of some categories and calculated the new profit. We decided to exchange the following product categories because they cover the same shelf space in Mini Mall, thus making it feasible:

• Chocolates (#38), Cakes & Croissant (#39), Biscuits (#36) located originally on the First Floor for which the initial characteristics and profit were found

• Deli Cheese (#24), Chicken (#27), Meat (#26), Chilled Fish (#29) and Kashkaval (#31) originally located on the Ground Floor

The initial profit generated from impulse purchase by these 8 categories amounts to 447,759 LBP. After exchanging them, the new calculated profit is 911,200 LBP thus generating a 103.5% increase in impulse purchase's profit and proving that our model is viable. Table IV shows a sample of the values of Chocolate (#38) before and after exchanging. It can be noticed that *traffic intensity* and *visibility rates* drastically change, while *impulse rates* remain the same because it is independent.

TABLE IV. INITIAL AND FINAL VALUES

p	Profit Margin	Sales Volume	t_e	n_e	i_p	Profit
Chocolate (before)	0.16	20997872	0.107	0.642	0.65	150012
Chocolate (after)	0.16	20997872	0.0279	0.725	0.65	44172

Fig. 5 shows the Ground Floor after exchanges, which can be compared directly to Fig. 1. The Heat Maps of other floors are included in the official report.

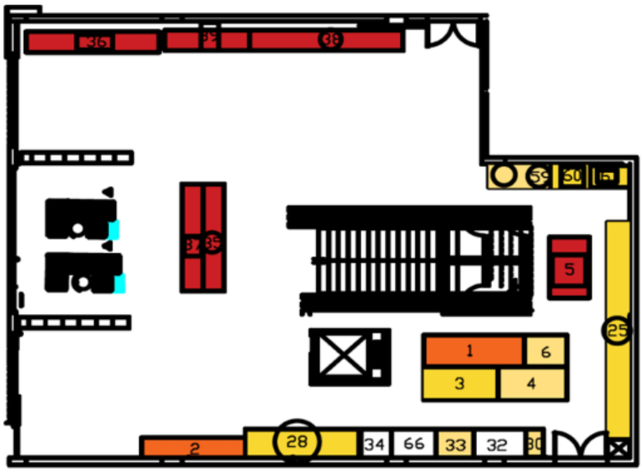

Fig. 4. Ground Floor after exchanging the two sets of product categories

VI. Discussion and Conclusion

A. *Insights and future work*

The manual changes made achieved a significant increase in impulse purchase profits. Such heuristics prove the feasibility of our objective, which is to increase Mini Mall's profits through impulse buying, but don't give us the maximal profit. For the profits to be maximized, all product-shelf combinations should be tested followed by shelf-location assessment. For this reason, we are now working on solving the optimization model using AMPL and CPLEX, which is the last aim required to complete our first objective. We are able to do this because we have already collected all the data necessary as input for the model (profit margins, sales volume, traffic intensity/visibility/impulse purchase rates).

B. *Limitations*

The survey sample size was only 108 samples and one question due to lack of resources (time and money); however the results were realistic. Also, the current situation in the country affected the behavior of customers and in a way that it had decreased products' impulse purchase rates; the roadblocks affected our ability to access the facility as much as needed.

The objective function we are using to optimize the profitability can be more complex resulting in better optimal solution but, as undergraduates, we will not be able to solve its complexity. We assumed that the traffic intensity at a shelf depends on the shelf location only. A better model would have traffic intensity depending on shelf location and the products assigned to the shelf. The inputs used in the objective function such as the traffic intensity could have been calculated using beacons mounted on trolleys or camera analyzing software's but we do not have the means therefore we used the reciprocal of the distance from the entrance.

C. *Conclusion*

To conclude, the product categories' allocation across different shelves and aisles in a supermarket do affect impulse buying. After checking the feasibility of our model through manual changes, our goal is to execute the model and find the optimal allocation leading to maximized profits. In order to further optimize Mini Mall, our next objective is to improve customer satisfaction by reducing bottlenecks at cashier counters using simulation techniques.

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