Optimization of Block Layout for Grocery Stores

by

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Abstract

Because of the proportion of the retail industry worldwide of the global economy and the lack of analytic approaches in the literature to retail facility design, this dissertation addresses block layout in grocery stores with the participation of Migros, a major Turkish retailer. The goal is to develop an effective method for solving realistic grocery store block layout problems which consider revenue and adjacency. The main difference between previous research and this proposed research is the integration of stochastic simulation and optimization together to solve the layout problems modeled specifically for grocery stores. Actual data and insights from Migros are also incorporated into the methodology.

This project is divided into two main parts. The first part is the revenue assessment of store layout using stochastic simulation considering impulse purchase rates and customer traffic patterns. Using market basket data from Migros a methodology is developed to identify groups of departments where the products are often purchased concurrently. This, in turn, is used to estimate the impulse purchases of customers. In the second part, optimization is used by considering limited space requirements, unit revenue production and department adjacencies. As an optimization tool, because of the strong neighborhood structure and complexity of the problem, a tabu search algorithm is used and compared with two simple constructive heuristics. The candidate layouts generated in this step are evaluated by discrete event stochastic simulation. As we have multiple objectives to maximize, a bi-objective model is formulated for the store with the concurrent objectives of revenue maximization and adjacency satisfaction. A set of non-

dominated designs are generated by the tabu search for a decision maker to consider further. This approach is both effective and pragmatic for optimal design of grocery store block layouts.

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There is no word that can express how I am thankful to her, my unconditional lover, forever supporter and most precious gift of the God, my mom. She never gives up and always

supported me during this hardest time of my life. She believes me more than myself and lightened my dark days with her lovely hearth. I dedicate this dissertation to her.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

COP	Computational Optimization Problem
CRM	Customer Relation Management
FLP	Facility Layout Problem
GSLP	Grocery Store Layout Problem
MIP	Mixed Integer Programming
QAP	Quadratic Assignment Problem
QSP	Quadratic Set Covering Problem
TS	Tabu Search
MTS	Multi-nomial Tabu Search

Chapter 1

Introduction

Retailing, selling goods to buyers for their own or family use, occurs in various venues, such as department stores, like Dillard’s and Macy's; discount stores, like Wal-Mart and K-Mart; and specialty stores, like The Gap and Toys 'R' Us. On-line stores, like Amazon.com and Overstock.com, also sell retail *(*www2.fiu.edu/~retail/whatis.html). The retail industry, one of the biggest sectors of the economy, involves more than 1.1 million businesses in the U.S. and over 42 million employees - 1 in 4 American workers (www.nrf.com).

According to a 2012 Global Powers of Retailing report, supermarkets and grocery stores serve as the largest retail chains in 14 countries around the world. Out of total grocery sales world-wide of more than $2.7 trillion/year, the U.S. retail grocery industry of about 65,000 stores has combined annual revenue of about $620 billion (http://www.fmi.org/research-resources/supermarket-facts). Our study models and solves an important and common facility layout problem for the retail industry - the grocery store layout problem (GSLP).

The supermarket industry, faced with the challenges of maintaining market share and profits, must develop new concepts and store formats to differentiate itself from other retailers. Grocery chains make major investments to build new stores and remodel existing ones; to build a new store; food retailers invested an average of $6.5 million in 2006 or $146.70 per square foot (http://www.fmi.org). In 2008, more than 60 percent of retailers planned to build new stores and 77 percent planned remodeling. Industry experts estimate a typical store requires remodeling ten years after it opens and every six to seven years thereafter to improve its looks, efficiency and operation (http://www.fmi.org).

Research in the retail industry has generally involved more qualitative studies than quantitative. Although decades of studies have looked at facility layout problems, most of the previous research on the topic has focused on the manufacturing industry (Yapicioglu, 2008). Recently, facility layout problems in service industries, such as hospitals, have received more attention because of the need to improve customer satisfaction and the increasing competition among providers (Chen, 2010).

The layout of a store plays a big role in a customer's store experience; a customer may decide whether to return to a store based on this impression. From a retailer's perspective, the store layout determines a customer's exposure to goods and thus affects the chances of the customer buying certain goods. Except for some intuitive guidelines used by retailers in store layout design (for instance, to locate coffee and sugar together or shampoo and conditioner together), the number of analytical layout design models for retail stores in the literature is limited.

The need exists for developing a systematic procedure of layout planning in retail stores to provide a competitive advantage to the retailer (Inglay and Dhalla, 2010). Therefore, in this study, we develop a layout model for grocery stores (defined under the food retail sector) and propose a solution methodology. Migros is the first name to come to mind when considering the modern retail sector in Turkey. The company operates a total of 1155 stores, with 851 Migros, 212 Tansaş, 27 Macro Centers, 24 5M's in 70 provinces of Turkey, and 41 Ramstores abroad, spanning a total area of 1.588.189 square meters (www.migroskurumsal.com).

As Migros has a wide range of products and store layouts, opportunity exists for more research beyond this project. Furthermore, Migros has an abundance of data about their customers and sales from their SAP (Systeme, Anwendung und Produkte) system, and the managers appear open-minded and ready to change. Mr. Özgür Tort, the CEO of Migros, championed this project and assigned his staff to work with us on it.

1.1 Problem Definition

A good layout seeks to balance the needs of both customer and retailer at the same time. "Allocating sufficient space to the departments and placing those related close to each other can have substantial impact on the retailer's profitability" (Yapicioglu, 2008). A good design should encourage buying more than planned. The layout should not be too complex, however, for customers to find the products they want to buy (http://www.fmi.org); this means creating a positive shopping experience for consumers, inviting return visits while maximizing chances for impulse purchases.

“Impulse purchase is the difference between the product purchased and the products planned to be purchased before entering the store” (Kollat and Willet, 1967) and is essential to increasing sales. Different product categories have different impulse purchase rates (McGoldrick, 1982). Thus, the location of products with high impulse purchase rates should lie in high customer traffic areas in the store to increase revenue due to impulse purchasing (Botsali, 2007).

We seek to formulate and to solve the block layout problem for grocery stores. This design specifies the sizes and the relative locations of departments in a retail store. Many approaches have arisen to model the block layout problem in manufacturing. Differing from manufacturing systems, however, humans comprise the main entity of the retail system, so we must consider other factors than material handling cost. More specifically, the primary objective is to maximize revenue or profit.

Most of the approaches used so far, both in practice and in the literature, use only qualitative approaches or only quantitative approaches in the solution process of retail layout problems (Peters et. al., 2004; Botsali and Peters, 2005; Yapicioglu and Smith, 2012). Some rely on simulation models to study qualitative factors, and others consider optimization, but none has combined simulation with optimization capabilities. In this study, real data from the Migros Company, as well as meetings and interviews with company managers, shaped the model. Based on their prior experiences, the managers set the impulse purchase rates of product categories. From the market basket data, we defined related product groups and generated an adjacency matrix; stochastic simulation proves a basis for comparison of block layout. The simulation model takes into account impulse purchase rates and location effects. Then, to improve the current layout, we designed heuristic methods, specifically a constructive heuristic and a tabu search for both single and multi-objective models. Considering non-dominated layouts according to total revenue and adjacency score, gives multiple options to the decision makers.

1.2. Research Objectives and Primary Contributions

This research looks at the influence of layout in the grocery industry; more specifically, we seek to develop an effective method for solving realistic grocery store block layout problems. The two main parts of the project include the following:

1. Characterization of store layout using stochastic simulation considering impulse purchase rates; and
2. Optimization of store layout with a Tabu Search Algorithm by considering space requirements, revenue and department adjacencies.

Due to the complexities of shopping behaviors at Migros, the development of a stochastic simulation model allows detailed analysis of any given store layout. With known dimensions of the store and constraints on the department areas, in the optimization we consider changing the size of existing departments. A tabu search algorithm generates candidate layouts to evaluate in simulation; this step involves the adjacency preferences of the company, so we formulated a bi-objective model maximizing both revenue and adjacencies. We identify Pareto optimal designs since there are two objectives.

This research contributes to the literature by:

- Developing model(s) reflecting real grocery store block layout situations;
- Optimizing layout of departments by taking into consideration area constraints and adjacency preferences;
- Developing a model maximizing the total revenue incorporating impulse purchase rates; and
- Interfacing stochastic simulation with heuristic methods.

Questions answered at the end of this research include the following:

- The most profitable layout for the company?
- The most comfortable layout in the measure of adjacency score?

- The area needed by each department for proper space utilization and revenue maximization?

1.3. Organization of the Dissertation

The remainder of the dissertation begins with Chapter II, a literature review of facility layout problems, including retail industry and grocery store layout problems. Chapter III introduces a specific grocery store layout problem, the main issue of this research. A stochastic simulation model of Migros appears in Chapter IV. In Chapter V, we analyze market basket data from Migros and generate an adjacency matrix used in the optimization section. Chapter VI includes constructive heuristics and single-objective and bi-objective tabu search algorithms, along with an evaluation of the new layouts obtained from the heuristics using the simulation model. Finally, Chapter VII concludes with extensions and potential future work based on this research.

Chapter 2

Literature Review

This section contains a review of the previous work in the literature. The literature is categorized in the following sections: the facility layout problem and solution methods, the retail industry and grocery store layout literature, and the impulse purchase literature.

2.1. The Facility Layout Problem

“A facility is a piece of equipment such as workstation in a manufacturing system or a department in an organization which makes it possible to produce goods or provide particular kind of service easily” (Moslemipour et al., 2012). “The facility layout problem (FLP) is the optimal placement of a set of departments with known dimensions within the facility area, in order to minimize the operating cost and maximize the system efficiency” (Aiello et al., 2012).

As a very well-known Industrial Engineering problem, with numerous articles published in this area, the FLP looks simple in description, but it remains very difficult to solve. For this reason many researchers have paid attention to this topic and have proposed different solution methods. A recent review study done by Drira et al. (2007), created a tree representation of the different factors taken into account in FLP; it appears in Table 2.1. The table illustrates the objective functions, the types of facility layout problems, and the exact methods or heuristic methods used as solution tools.

The literature in this area focuses on manufacturing systems and especially on material handling systems. A few people recognized the gap in service system layout problems, and the number of papers in this area has recently increased (Peters et al., 2004; Botsali and Peters, 2005; Yapicioglu, 2008; Li, 2010; Bruzzone and Longo, 2010; Yapicioglu and Smith, 2012; Ozcan and Esnaf, 2013). Some specific differences exist between manufacturing systems and service systems. “The most basic distinction between manufacturing facilities and retail facilities is that in the latter the traffic is mostly human. Hence, the traditional performance measure of cost minimization is not appropriate” (Yapicioglu and Smith, 2012).

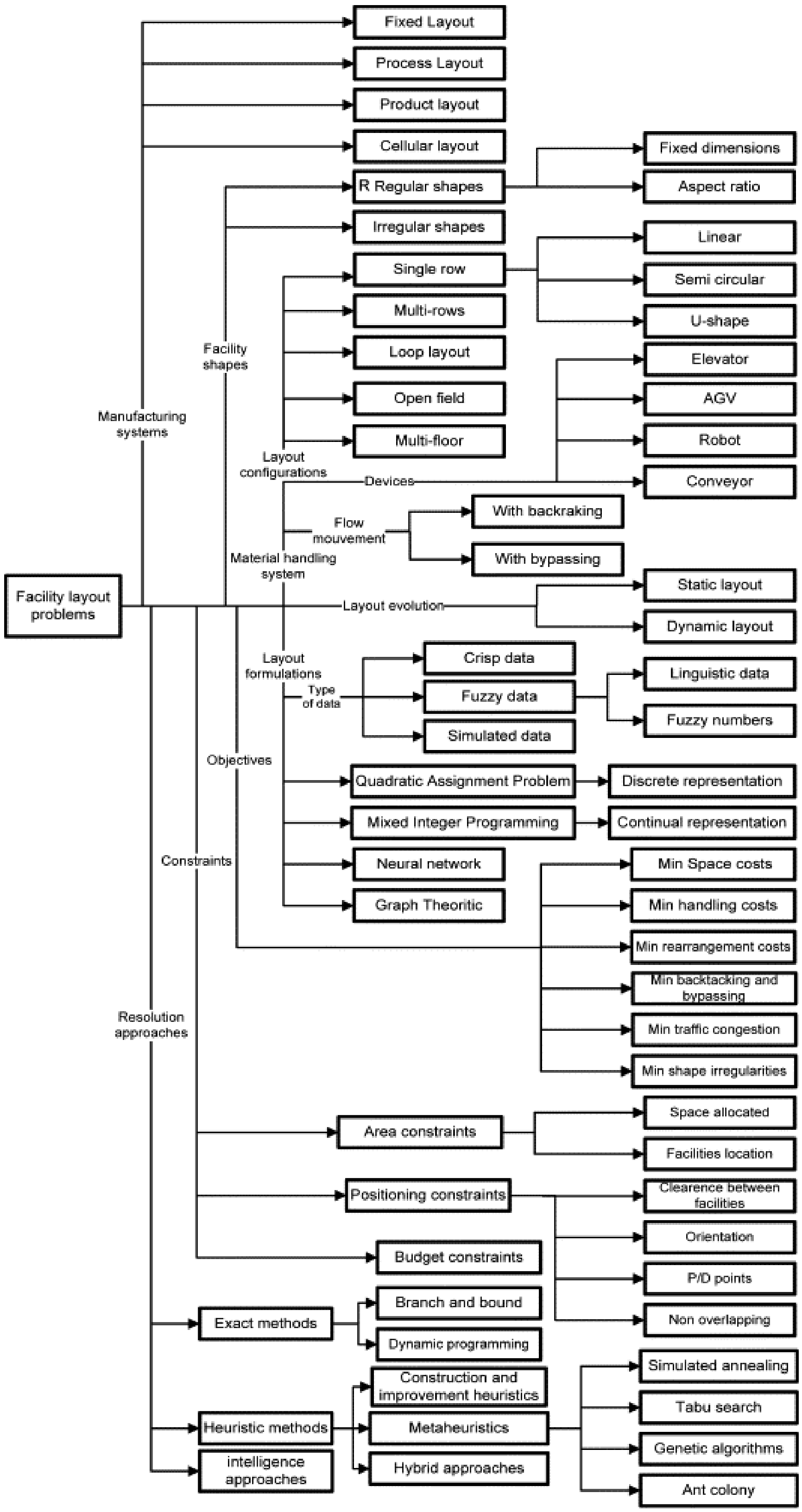

Table 2.1: Tree representation of facility layout problems (Source: Drira et. al., 2007)

How to model the facility ranks as another important issue in FLP. While research has developed many models, the most commonly used ones include 1) the block layout model and 2) the graph theory model. The block layout model considers the spatial dimension of the FLP, while the graph model focuses on the interactions among departments. For GSLP, we model the problem as a block layout.

Depending on the problem, the representation of the layout can appear discrete or continuous, as shown in the figure below.

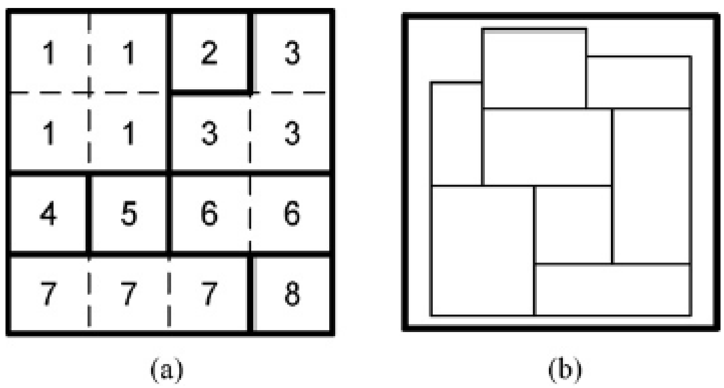

Figure2.1. Discrete and continuous layout representations (Drira et al., 2007)

The discrete representation of the layout, divided into unit squares (grids are not always one unit square), has generally seen formulated as a quadratic assignment problem (QAP). Many authors have studied the QAP with departments equally sized and equally shaped; in real life, however, the facilities do not have identical department. In 1975, Bazara developed a new problem solution model- the quadratic set covering problem (QSP). "In this problem, the entire area is divided into smaller blocks so that each facility is divided into just one location and each block is considered to have at most one place."(Kusiak and Heragu, 1987; Moslemipour et al., 2012).

When continuous, the layout representation has no grid structure and has often seen treatment as a Mixed Integer Programming Problem (MIP) (Montreuil, 1990). Continuous representation provides flexibility but is more difficult to model and to solve. All of the departments, placed within the planar site, must not overlap each other (Drira et al, 2007). Although the MIP formulation has power, due to the large number of binary variables and area constraints from the structure of the model, practitioners prefer heuristic solutions to optimal solution methodologies (Yapicioglu, 2008).

Before giving more information about service layout and the retail industry, we will make a short review of the existing solution methods developed for manufacturing FLP in the literature. One sees FLP usually modeled as a combinatorial optimization problem (COP), and a COP appears as an optimization problem with a finite number of feasible solutions (Winston, 1991). A solution occurs for many COPs (non-deterministic polynomial (NP)-complete problems) only in computational time exponentially proportional to the size of the problem (Moslemipour et al., 2012). No single best approach exists to solve FLP; in general, categories of approaches include the following: a) exact (optimal) methods, b) problem specific heuristic methods, c) meta-heuristic (general purpose) heuristic methods.

2.1.1. Exact Methods

Exact methods include a) branch and bound, b) cutting plane and c) dynamic programming algorithms. Branch and bound solves problems by branching into smaller sub problems; one prunes the branches with non-improving solutions or infeasible solutions until finding the optimal solution. Gilmore (1962) and Lawler (1963) first proposed using branch and bound algorithm; they solved the FLP formulated as a quadratic assignment problem. Meller et al., (1999) also used this approach to solve the problem of placing rectangular facilities within a given rectangular available area. They proposed general classes of valid inequalities, based on an acyclic sub-graph structure, to increase the range of solvable problems and used them in a branch-and-bound algorithm.

Bazaraa and Sherali (1980) proposed the cutting plane algorithm for an FLP. This algorithm cuts off continuous regions by adding a constraint to the model and can solve the FLP formulated by QAP with a maximum of 25 departments.

One would usually use the dynamic programming algorithm to solve for multiple time periods; Rosenblatt (1986) used it to solve a FLP with equal size facilities. Only small problem instances, however, have found optimally (six departments and five time periods).

2.1.2. Heuristic Methods

Since one finds exact approaches usually unsuitable for large size problems, numerous researchers have developed heuristics. Heuristic methods can produce a good quality solution for FLPs in a reasonable computational time (Kusiak and Heragu, 1987). Basically, one can categorize heuristic methods into two groups: a) construction algorithms, and b) improvement algorithms.

Construction algorithms produce a single solution from scratch by selecting and locating one facility at a time (Moslemipour et al., 2012). "These algorithms are regarded to be the oldest and simplest heuristic methods to solve the QAP models from a conceptual and implementation standpoint; however, they might not generate solutions with reasonable quality" (Singh and Sharma, 2006).

Improvement algorithms usually use a randomly generated initial solution and, based on this solution, systematic changes to the design. Evaluation of the result leads to retention of the change with the best design and the procedure continues until no more improvement occurs. As expected, the solution quality depends upon the initial layout. CRAFT, COFAD and revised HILLER exemplify improvement algorithms (Shouman et. al., 2001).

2.1.3. Meta-heuristic Methods

Many researchers have proposed exact optimization algorithms to address optimization problems; these algorithms lack efficiency, however, in solving larger scale combinatorial and highly non-linear optimization problems (Behesthi and Shamsunding, 2013). Therefore, the literature has proposed a set of more adaptable and flexible algorithms usually inspired by natural phenomena.

"A meta-heuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems." (Dorigo and Stutzle, 2004). Meta-heuristic algorithms have an incremental ability to solve a variety of hard COP's (such as FLP) by finding very good quality solutions in reasonable computational time (Jones et al., 2002). Some of the meta-heuristic approaches used in FLP include genetic algorithms, tabu search, simulated annealing, ant colony optimization, and particle swarm optimization. According to the review of Jones et al., (2002), there is a significant grow in the number of papers that studies multi-objective meta-heuristic models in the literature after 1991 due to the increased computing power and increased awareness of the importance of multiple objectives in many disciplines.

In our study, because of the complex nature of the problem and the strong neighborhood structure, tabu search algorithm works well. Tabu Search (TS), a meta-heuristic, guides a local heuristic search procedure to explore the solution space beyond local optimality (Glover and Laguna, 1997). Glover (Glover, 1986, 1989, 1990; Reeves, 1995; Glover and Laguna, 1997) introduced it in the combinatorial optimization literature. Successful implementation has occurred in many areas including the following: quadratic assignment (Taillard, 1991), unequal area manufacturing facility layout (Kulturel-Konak et. al, 2004), vehicle routing (Taillard et. al, 1997), redundancy allocation (Kulturel-Konak et. al, 2003), job shop scheduling (Barnes and Chambers, 1995), and weighted maximal planar graphs (Osman, 2006).

TS, basically a single-solution deterministic neighborhood search technique, uses memory (a “tabu list”) to prohibit certain moves, even if improving; this feature makes it a global optimizer, rather than a local optimizer (Glover, 1995). Another main feature of TS involves responsive exploration-“intentional selection of worsening moves to gain better understanding of the fitness landscape.” (Glover, 1995).

In a canonical TS, in each iteration, the algorithm selects the best move. “In some cases, however, if a tabu move improves upon the best solution found so far, then that move can be accepted. This is called an aspiration criterion” (Kulturel-Konak et. al., 2006). The tabu list updates while investigation of the best candidate occurs, and the entire process starts again. The search continues until a predetermined stopping condition (Kulturel-Konak et al., 2006).

Intensification and diversification strategies comprise two important components of a tabu search. “Intensification strategies are based on modifying choice rules to encourage move combinations and solution features historically found good. They may also initiate a return to attractive regions to search them more thoroughly” (Glover and Laguna, 1997). Additionally, diversification strategies ensure exploration of different regions of the search space for better solutions (Balakrishnan and Cheng, 1998). During an intensification stage, the search focuses on examining neighbors of elite solutions- the basic difference with diversification (Glover and Laguna, 1997).

Many methods exist for solving a FLP. “TS is used to solve the facility layout problem because of the existence of non-linearities in the objective function and/or the constraint set, the strong and consistent neighborhood structure of the block layout and the necessity for a global, rather than local, optimizer” (Kulturel-Konak et.al., 2007).

Skorin-Kapov (1990) conducted the first application of a tabu search algorithm for a FLP. The problem, formulated as a QAP, led to better results on standard test problems than any other solution method previously known in the literature. Taillard (1991) also used TS for QAP. After the success of the algorithm for static facility layout problems, Kaku and Mazzola (1997) presented a TS for the dynamic facility layout problem. Since then, TS has commonly served as a tool for the solution of many layout problems.

Currently, most leading research in tabu search makes use of advanced concepts and techniques; a large part of the recent research in tabu search concerns various techniques for making the search more effective. “These include methods for better exploitation of the information that becomes available during search and creating better starting points, as well as more powerful neighborhood operators and parallel search strategies.” (Gendreau and Potvin, 2005).

The literature on tabu search has also started moving away from its traditional application areas (graph theory problems, scheduling, and vehicle routing) to new ones: continuous optimization (Rolland, 1996), multi-objective optimization (Gandibleux et al., 2000), stochastic programming (Lokketangen and Woodruff, 1996), mixed integer programming (Crainic et al., 2000; Lokketangen and Glover, 1996), and real-time decision problems (Gendreau et al., 1999). Researchers still look for new areas to implement the TS algorithm; our study in grocery store layout serves as the first application of TS in this area.

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2.2. The Retail Industry and Layout

"The retail industry environment is characterized by intense pressure of competition, ever-changing portfolio of products, hundreds of different products, ever-changing customer requirements and be able to compete in a mass market." (Buyukozkan and Vardaroglu, 2012). This sector's main features include dynamism and competition.

"Studies in environmental psychology and retailing testify to the importance of environmental design for creating pleasurable consumer experiences, conveying a desired store or service image, and promoting specific behaviors." (Van Rompay et al., 2012). Retailers and manufacturers, very interested in how shoppers make their purchase decisions, consider when, why and whether a shopping trip leads to a purchase. This information becomes critical in formulating marketing strategy (Kotler, 2000) and in retailing planning (Levy and Weitz, 1992).

Grocery stores sell a variety of products that are consumed such as soft drinks, dairy, household and cleaning supplies. These products are grouped together by similarities as sub product categories. These, in turn, form main product categories. For instance, soft drinks is a department (main product category) of which soda is a product category and light soda is a product under this category.

Two of the more important decisions made by retail store management consist of the store layout, and the sizing and locations of product categories. "Store layout refers to the positioning of physical elements such as racks and product displays throughout the store environment" (Van Rompay et al., 2012). Layout, a tangible spatial-design factor directly impacting behavior, differs from non-tangible ambient factors, such as color (Van Rompay et al., 2012).

Retail floor layouts strongly influence the in-store traffic patterns, shopping behavior, shopping atmosphere and operational efficiency. In conventional retailing, some of the more common store layouts include grid, freeform, and racetrack layouts (Levy and Weitz, 2008). Grid layout, a rectangular arrangement of displays, has parallel aisles with merchandise on shelves on both sides of the aisles (Levy and Weitz, 2008); this design finds wide use in the grocery sector because customers generally plan their purchases before visiting the store. The advantages of a grid layout include having minimal wasted space, cost efficiency ("because the interior fixtures can be standardized and a great deal of product can be displayed per square foot", (Murray, 2013)) and the ease of finding products (Ozcan and Esnaf, 2013); on the other hand, restricted stimulation and boring arrangements can occur.

The freeform layout, mainly used by name brand stores in fashion industry, like American Eagle, Ann Taylor , lets customer move in any direction in the store and spend a lot of time in the store. Flexibility and relaxing environment favor this layout, but not space efficiency.

In the racetrack layout, the floor divides into individual areas along a main aisle in the middle of the store facilitating customers' movements through the facility. The layout appears in department stores, such as Kohl's and Sear's; it strongly encourages unplanned purchasing (Ozcan and Esnaf, 2013; Yapicioglu, 2008). General design of the store layout occurs by choosing one of these three classes or by mixing them in relation to item typology and consumer behavior (Bruzzone and Longo, 2010).

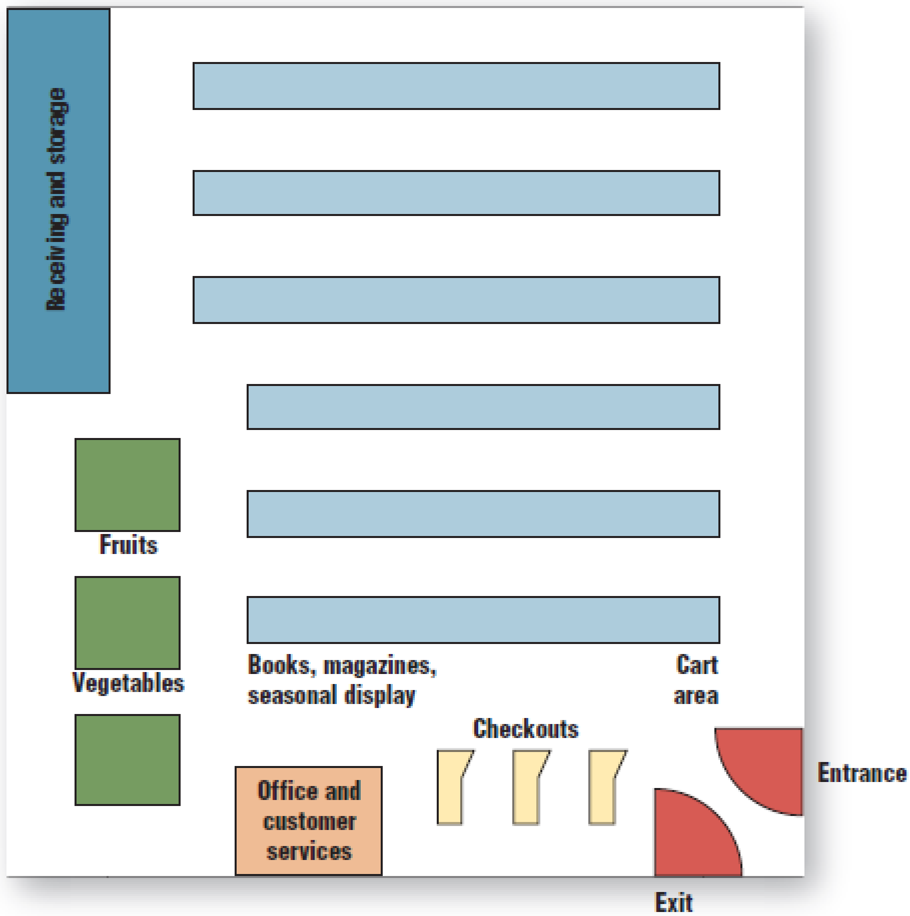

Figure 2.2: Grid Layout (Levy and Weitz, 2008)

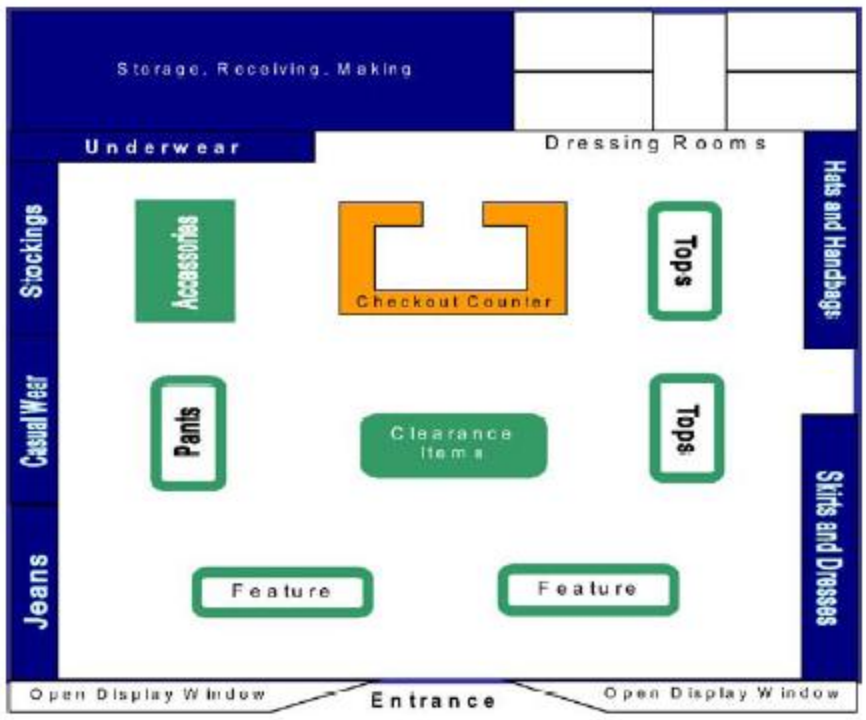

Figure 2.3: Free-form Layout (Levy and Weitz, 2008)

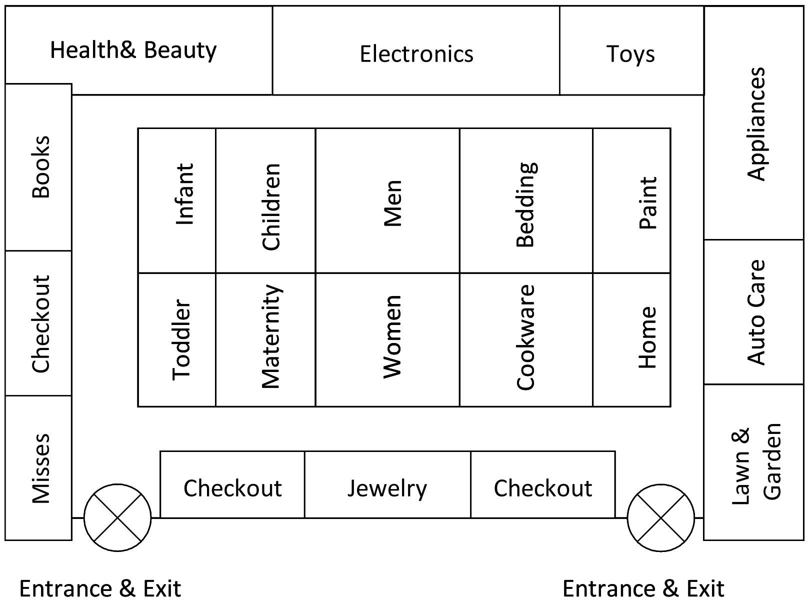

Figure 2.4: Racetrack Layout (Yapicioglu, 2008)

2.2.1. Retail Store Layout Literature

After the product assortment decision, retailers have to determine the locations of each selected product in the store- a significant factor that affects the sales (Hariga et. al., 2007; Ozcan and Esnaf, 2013). Providing an uncomplicated layout and making shopping easy can increase potential revenue and encourage store image.

Some standard guidelines used by retailers in store layout design include locating coffee and sugar together or shampoo and conditioner together; displaying some product pairs side by side increases the unplanned purchasing of customers (Abratt and Goodey, 1990). Despite these intuitive guidelines, no analytical layout design model exists for retail stores in practice.

Although a large literature exists on manufacturing facilities or warehouses, very few publications relate to retail store layout (Yapicioglu and Smith, 2012; Ozcan and Esnaf, 2013). A new study from Mari and Poggesi, (2013) states, of 188 articles, only 22 articles cover shelf space, product display and retail layout topics in related journals.

The first study addressing the retail store layout problem came from Botsali and Peters (2005) where the authors propose a network-based model for the serpentine layout for maximizing revenue by increasing impulse purchase. This model requires knowing customer shopping lists. Later, Botsali (2007) created several customer profiles and, for a grid layout, maximizes the expected impulse purchase of customers according to the locations of product categories.

Customers select items from a number of product categories on the same shopping trip and this decision making process in retail organizations, especially in supermarkets, is called market basket choice (Russell and Petersen, 2000). This information is valuable since it can be used to determine the placement of products. An interesting study by Surjandari and Seruni (2010) discovers associated products by using market basket analysis, and then uses this to determine the proposed product placement layout. A data mining process finds related products; for example, 90% of customers purchasing frozen pizza also buy soda. A retail store in Indonesia provided real data for 704 products from 25 product categories, defining relations such as drawing tools to toys, coffee to sugar, tea to sugar, cigarettes to candy, and cigarettes to chocolate; a proposed design of a product placement layout came from these category associations.

A recent study from 2011 (Uttke) reviews the factors affecting sales levels of food markets in today's world; new lifestyles in urban areas force supermarkets to act as a small city centers. "Today, supermarkets and discount food stores are more than places of supply. They are places to meet and greet those in the community. In the past decade however, as location and sale strategies are revised, many of these centrally located small- and mid-sized food markets close and more spacious and automobile-oriented locations are opened." Therefore, they have to analyze the new demands of customers and integrate this with the layout of the modern food store.

A Master's Thesis by Peng (2011) addresses the grocery store layout problem by maximizing the impulse purchase (unplanned buying) revenue. The author initially develops a p-dispersion based algorithm to spread the "must have" items in the store to increase impulse purchases. Then, a simulated annealing algorithm improves the grid layout by testing the effectiveness of the model. This study has some limitations, though. First, the store uses a grid layout, while most of the grocery stores in the real world have a mixed layout (grid and racetrack). Additionally, the dimensions of the departments appear equal in size or fixed (only taken into account in calculation of distance); in real world, the sizes of the departments vary according to the contracts with suppliers and the revenue of the department. These assumptions simplify the problem and make it less realistic.

A more recent study by Cil (2012) developed a new layout for a supermarket using association rule mining and multidimensional scaling techniques. The author clusters the products around customer buying habits by analyzing the transaction database. Instead of finding coffee in the beverage section, cheese in fresh cheese, and cornflakes in the cereal section, they propose a breakfast consumption universe. Other universes, such as the baby universe or tableware universe, propose the same scheme to cluster different product categories. The basic limitation of this study is not considering the area of departments. The difference between the current layout and proposed layout is the locations of departments.

A model and solution approach for the design of the block layout of a single-story department store is presented by Yapicioglu and Smith (2012). The model presented considers two criteria in evaluating a layout. These are the revenue generated by departments and adjacency satisfaction. The revenue generated by a department depends on the area allocated to the department (area effect) and the location of the department within the store (location effect). In this paper, the approach consists of placing departments in a racetrack configuration within the store subject to area and shape constraints. A general tabu search optimization framework for the model with variable department areas and an aisle network with non-zero area is devised and tested.

Another publication's of Yapicioglu and Smith (2012) proposes a bi-objective model for the retail design problem. Adjacency maximization and revenue maximization are the two conflicting objectives of the model. Two meta-heuristic search methods, a multi-objective tabu search and the most well known multi-objective genetic algorithm, are used separately to solve the problem. The performance of these two heuristics is evaluated and compared, with results suggesting that the multi-objective tabu search is a better choice because of its ability to exploit the neighborhood structure of the model.

A recent study from Aloysius and Binu (2013) presents an approach to product placement in supermarkets using the PrefixSpan algorithm. The authors aim to increase impulse purchases and profit by searching user buyer behavior. The proposed approach mines the patterns in two stages. In the first stage, the sequences of product categories are mined to place the product categories on the shelves based on the sequence order of mined patterns. Subsequently, in the second stage, the patterns (products) are mined for each category and then products are rearranged within the category by incorporating a profit measure based on the mined patterns. The basic limitation of this study is the experimentation is carried out on small synthetic datasets. Also instead of using an objective function such as maximizing revenue or profit, the authors define a measurement called "profited sequential pattern" which is combination of support value and profit of the product. In spite of these limitations, the evaluation using two datasets showed that the proposed approach is good for product placement in supermarkets.

Finally, as an example of the retail store layout problem, Ozcan and Esnaf (2013) consider bookstore layout optimization using genetic algorithms. They first propose a mixed integer mathematical model and then, for a real bookstore design, develop a heuristic approach based on genetic algorithms. In their model, to determine the shelf locations of the products they used association rules. There are specific shelf space constraints valid only for bookstores. They assume a grid layout and model it as a discrete constrained optimization problem. The objective is maximizing the retail's profit according to location effects. The approach was applied to a bookstore with 137 shelves and 30 product categories. They compared the results with tabu search (TS) based heuristic and concluded that genetic algorithm(GA) based heuristic is better than TS based heuristic in terms of solution quality however, the TS based heuristic is superior to the GA based heuristic in terms of average CPU time.

2.3. Impulse Purchase: Unplanned Buying In Supermarkets

The revenue of a grocery store depends on the number of products that customers purchase. Although most customers have predetermined item lists before shopping, 30 to 50 % of sales come from impulse purchases (Bellenger et al., 1978; Kollat and Willett, 1967; Mishra and Mishra, 2010)- defined as a purchase decision made in-store with no articulated need for such a purchase prior to entry into store (Kollat and Willet, 1967; Bellenger et al., 1978; Abratt and Goodey, 1990.)

According to the research of Mathematical Association of America (2005), 81% of shoppers come to a grocery store with either a physical or a mental shopping list. It is also stated in the same research that each week consumers spend an average of 1.5 hours grocery shopping during 2.5 trips to the grocery store; 85% of their purchases replenish staple items. Consumers have identified quick and efficient shopping as one of the most desired traits in their evaluation of grocery stores, and shoppers' evaluations of stores affect their degree of loyalty. Milk, meat, paper products, frozen foods and breads/cereals serve as the most popular "must-have" items on a customer list, but most shoppers will buy items not included on their list. "The more items a customer passes while shopping for "must-haves", the more impulse buys a customer will make" (http://mathdl.maa.org/images/upload_library/4/vol6/online/groceryproject.pdf). Increasing the likelihood of "impulse" purchases by customers therefore increases revenue.

Impulse buying in supermarkets interests both manufacturers and retailers when they evaluate customer purchasing behavior and the effectiveness of the design of the store that stimulates additional sales.

When we look at the literature, three studies concern impulse purchases in supermarkets. The Popai/Dupont Consumer Buying Habit Study (1977) states, approximately 65% of all supermarket purchase decisions occur in-store, with over 50% of these unplanned. According to the Johnson and Williams (1984) study, an average of 20% of purchasing decisions occur inside the store, and this rate changes with product categories. Finally, Kollat and Willet (1984) made a study in eight stores of a national supermarket chain, and they found an average customer purchased 50.5% of products on an unplanned basis (Abratt and Goodey, 1990.)

The figure below, from a study of U.S. data from 434 households making over 18,000 purchases in 58 categories across 3,000 trips to 21 stores (Bell et al., 2009), gives information about impulse rates in a grocery store. As seen from the figure, baked food (cakes), frozen food and bath-shampoo-shave product have higher rate of impulse purchase than other product categories.

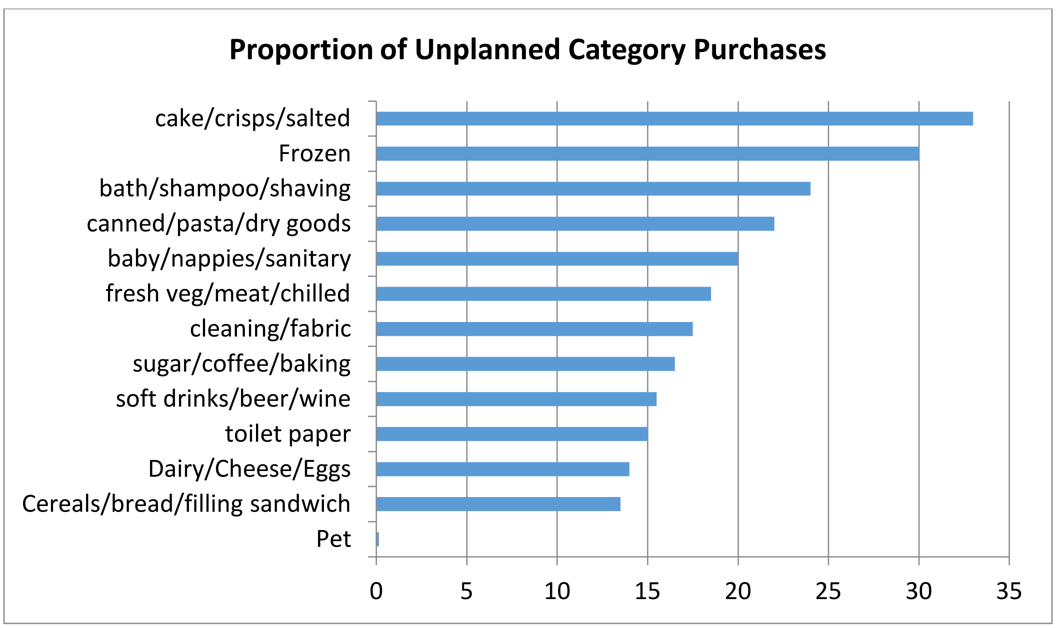

Figure 2.5: Impulse rates in a grocery store from Bell et al. (2009)

Impulse behavior differentiates across cultures. Abratt and Goodey (1990) analyzed the major supermarkets in South Africa and compared with similar studies in the United States and the United Kingdom. They found that unplanned buying is higher in the United States than in South Africa, but the importance of in-store stimuli is still strong on a multi cultural basis. In general, 47% of purchases in the U.S. fall in the unplanned category, with 20% for the U.K. and 23% for South Africa. In our study, personal experience of Migros store management sets the impulse purchase rate of the product categories.

When customers visit a grocery store, they typically purchase a basket of items containing a predetermined group of “must-have” items. Inclined to also buy “impulse” items purchased only if passed while shopping, the customer’s route during shopping strongly affects the number of “impulse” items purchased. The choice of customer travel path has received considerable attention. Farley and Ring (1966) developed a model to predict area-to-area transition probabilities for traffic in supermarkets and proposed a stochastic model of supermarket traffic flow. With the advent of new technologies, e.g., Radio Frequency Identification (RFID), researchers have better data to explore in-store shopping behavior (Guadagni and Little, 1983).

Kholod et al. (2010) investigated “the effect of shopping path length on sales volume” by designing a field experiment in a grocery store in Japan. The researchers collected data from 6,997 customers by using RFID tags and Point of Sale (POS) transactions. In the experiment, they questioned if longer shopping path result in sales growth. Consistent with previous studies, this article emphasizes that there is a positive relationship between the distance customers walk and quantity they buy.

A recent study from Hui et al., (2012) collected data from grocery store by using RFID tracking in conjunction to an entrance and exit survey. Based on a field experiment conducted in a medium-sized grocery store located in the U.S., “shoppers traveled around 1,400 feet (covering about 37% of the entire store), and the average amount spent on unplanned purchases was around $16, roughly 40% of their total shopping budget”.

Yaman et al., (2008) developed three different mathematical models in clustering shopping paths of customers for grocery store. The authors affixed a wireless video camera to the shopping carts of the customers in to understand “the mobility of shoppers, the most visited areas in the store, and the relationship between shopping trip and purchasing decisions”. The results of the models support the previous study of Larson et al. (2005) which found that the racetrack is the most visited zone in a grocery store.

Larson et al. (2005) categorized grocery paths using a clustering algorithm, and identified 14 different “canonical paths”. According to the study, the figure below shows a subset of the PathTracker data collected by Sorensen Associates, an in-store research firm, to understand shopper behavior in a supermarket. Customers tend to go back and forth from one department to another to find the items in their list, resulting in a lot of impulse purchases. Thus, grocery stores should carefully design their store to maximize product exposure to increase impulse purchases by customers.

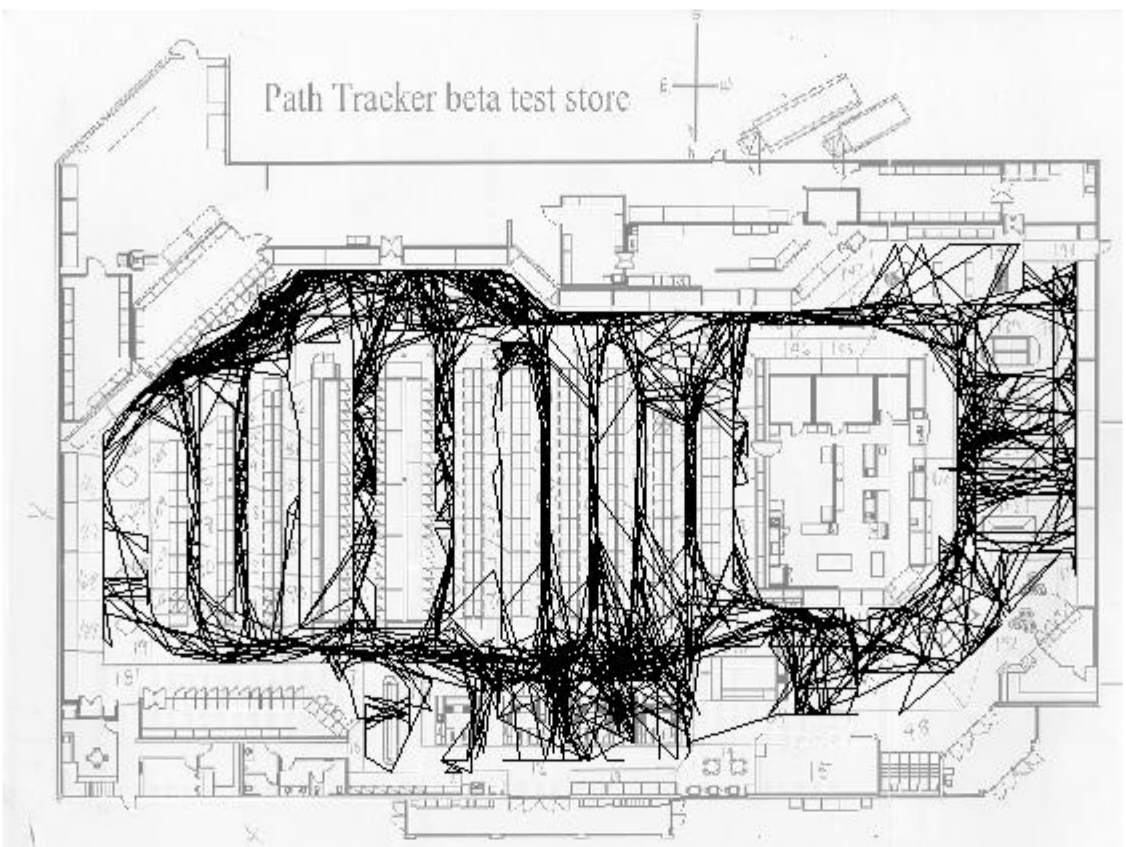

Figure 2.6 PathTracker data from 20 random customers from (Larson et. al., 2005)

As seen from Figure 2.6, customers do not regard all areas of the store equally; they pass throughout different areas of a shop with varying speeds, and certain areas of the store draw more attention than others. The most trafficked areas include following (Ozcan and Esnaf, 2013):

- Areas at the entrance of the store, especially the first shelf or other display areas where customers face immediately after entering the store.
- End caps of aisles -usually highly visible for people who do not enter into an aisle; and
- Check-out area, since all customers have to pass through -the preferred area for impulse items.

Also stimulating impulse purchases, adjacency pertains to a customer's tendency to buy items related to an item from his/her shopping list. Locating related items a certain distance apart would stimulate impulse purchases from merchandise displays positioned between a pair of related items. In the manufacturing sector, the main goal of minimizing material handling cost requires facility designers to locate departments with strong interactions close to each other. In the retail sector on the other hand, retailers may want to put related merchandise either close or far apart, depending on whether the retailer wants to shorten or lengthen the customer's travel path. Balance must occur between stimulating impulse purchases and increasing customer path length. (Ozcan and Esnaf, 2013)

To take into account the previous experiences of marketing managers regarding the impulse purchase likelihood of product categories and adjacency preferences, we interviewed the Migros store manager about his preferences. His ideas included the following:

- Locating the fish aisle close to the fruit and vegetables aisle will make customers spend time in the fruits aisle during the preparation of their fish orders;
- The textile aisle and cosmetics aisle should lie close together for women customers;
- The complementary canned food aisle and the lentils/oil aisles should lie close to each other.

These examples shape our optimization module and, coupled with an analytical approach, make our research unique.

Chapter 3

The Grocery Store Layout Problem

3.1. The Global Grocery Industry and the Turkish Grocery Industry

Global grocery and supermarket sales total more than $2.7 trillion per year. The leading 15 retailers, such as Kroger, Safeway and Supervalu, account for more than 30 % of worldwide sales (http://www.firstresearch.com/industry-profiles.aspx).The U.S. retail grocery industry includes about 65,000 supermarkets and other grocery stores with combined annual sales of about $620 billion. Consumer spending habits and food trends drive growth (http://www.fmi.org/ research-resources/supermarket-facts).

The retail sector, one of the fastest growing sectors in Turkey, increased from U.S. $70 billion in 2005 to U.S. $187 billion in 2010 (Nelson and Atalaysun, 2011). According to the Turkish Council of Shopping Centers & Retailers, the total sales area was 23 million square meters(sqm) and 1.8 million people found work in retail in 2010 (http://www.retail.org). The number of modern shopping malls in Turkey more than doubled in the last five years, from 129 in 2006 to 291 in 2011 (Nelson and Atalaysun, 2011).

Traditional shops filled the retail market in Turkey until 1990s. Then the opening of the supermarkets brought a new era in retail and reformed it in Turkey. “Currently, half of the retail sector in Turkey is still dominated by traditional retailers, large number of small-scale, independent and single location retailers. However there is a large room to grow for modern retailing in Turkey” (Ozdemir, 2012).

“Strong economic performance supported by a young population stimulates growth in spending per capita. As a consequence of the strong demand from Turkish consumers, Turkey became one of the most popular destinations for foreign investors including private equity firms, global supermarket chains, fashion retailers and several other retail concepts. By 2017, it is expected to have third highest growth rate after China and India (OECD).” (www.deloitte.com)

Internet sales have also become a focus for investors; a survey by TurkStat; Turkish Statistical Institute, shows 7% of internet users shop online in Turkey (http://www.portturkey). Furthermore, the report highlights Turkey as an emerging market- with its growing population, high level of urbanization and thriving middle class. It also mentioned the free market economy, low-cost labor and closeness to Europe as Turkey's strong points and underlined the value of the country as a production base for European markets. "Turkey will also benefit from the economic development in Russia, Central Europe and the Middle East", the report stated.

The sector should grow by 10% every year until 2016. (www.deloitte.com).These are huge numbers by any standards. Efforts to improve the efficiency and profitability of Turkish retailers will benefit the Turkish economy.

3.2 Migros Turk

As the largest factor in the Turkish retail sector, food retail had a market size of U.S. $96 billion in 2010 (Nelson and Atalaysun, 2011). While Turkish buyers in the past shopped mainly at small markets and grocery stores, consumers have moved toward supermarkets and hypermarkets offering a wider range of products and higher quality goods. The Turkish mass grocery retail market has become highly competitive (http://www.invest.gov.tr). An important assessment helping to explain the Turkish retail sector- local versus national and international supermarket chains- shows 168 local chains exist with a total of 3303 stores, whereas 21 national and international chains have a total of 8735 stores (http://gain.fas.usda.gov)

Migros has the largest share of the market at 9%, followed by Carrefour with 8 % and BIM with 7%; other international vendors include Metro, Tesco and Kipa (BMI Industry View, Turkey Food and Drink Report - Q2 2010). Migros Turk, Turkey's largest retailer, has become the first truly organized food retailer. As of July 11, 2014, it had a total of 1155 stores, with 851 Migros, 212 Tansaş, 27 Macro Center, 24 5M's in 70 provinces in Turkey, and 41 Ramstore stores abroad, covering an area of 1,588,189 sqm. Migros has been in the retail market since 1954, creating a wide sales network. The company uses this expertise to develop brand awareness, logistics capabilities, and procurement power. Moreover, its vast collection of data enables the pinpointing of localized consumer preferences and better understanding of market trends nationwide. The company grew by 11% in 2012, above the average for the sector, and plans to open 100 new stores per year, with half in smaller formats (www.migroskurumsal.com).

As a pioneer and innovator in the retail industry, Migros constantly upgrades stores and looks for better customer satisfaction. Because of our project's direct relation to both of these goals, the company agreed to share its data- not only informing our project, but also helping narrow academia's gap between practice and research.

3.3. The Grocery Store Layout Problem

In our case study, store data came from the Capitol Migros store in Istanbul, Turkey, a middle sized grocery store (1200 square meter, "2M") located in a shopping mall with eleven straight grid aisles, a racetrack aisle, one entrance and one exit; the layout appears in Figure 3.1.

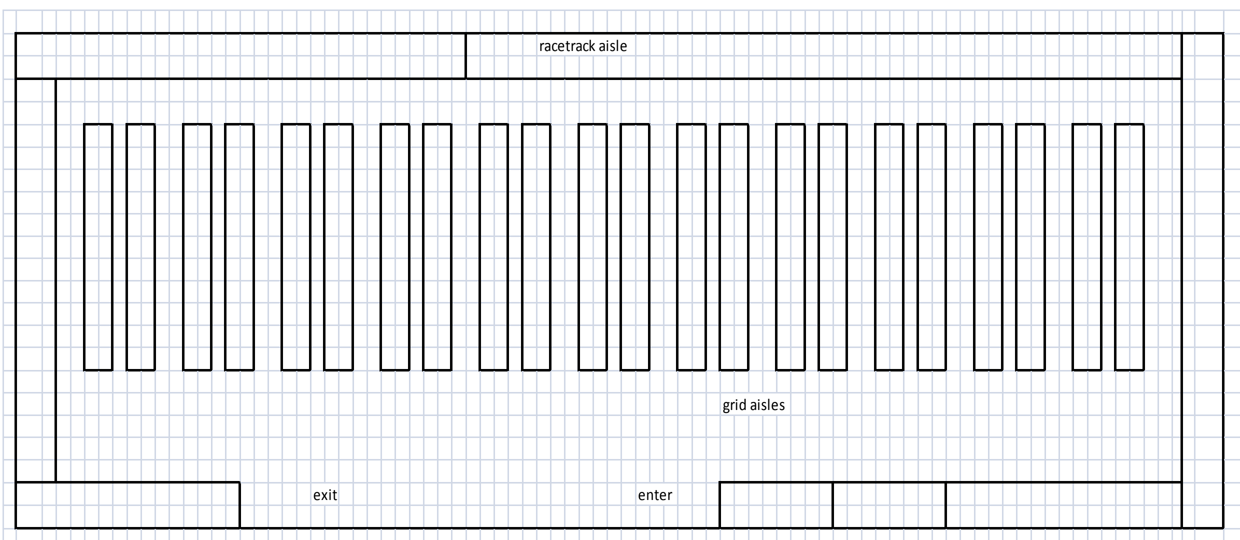

Figure 3.1 Simple layout representation of Capitol Migros Store.

The layout decision involves the location of the departments and the departments' length. The racetrack aisle is the major aisle that loops around the store and has a fixed length. Grid aisles are inside the store and have also fixed length. The departments are placed within these aisles by considering the adjacencies and the unit revenue of the departments.

3.3.1. Objectives

In retail, stakeholders include retailers, suppliers and customers- each with different concerns; this diversity of interests led us to search for an optimization model balancing conflicting objectives. The company seeks to increase sales and revenue, while minimizing the cost of its retail space. On the other hand, customers want an easy and comfortable shopping experience with low prices.

The main objectives include following:

- To develop a model maximizing the revenue generation with respect to layout in grocery stores (space optimization and maximization of impulse purchase); and
- To maximize customer satisfaction by designing a comfortable store by considering the adjacencies of related departments (maximization of adjacency score).

Chapter 6 contains information about the resulting multi-objective model.

3.3.2. Constraints and Assumptions

We addressed the following model constraints:

1. The space assigned to departments must equal or exceed the minimum space set by the supplier and retailer.

Grocery stores have meat, poultry, dairy, and bakery aisles, along with shelf space reserved for canned and packaged goods and various non-food items, such as household and cleaning supplies; the Capitol Migros store has 3783 different products. Grouping these products together by similarities (sub-product categories) forms main product categories, in turn generating departments within the store. For instance, “alcoholic drinks and tobacco” as a department has beer as a product category and light beer as a sub-product. Since we consider a block layout problem, we focus on departments in this dissertation; each department has a minimum area constraint directly related to a decision between suppliers and the retailer. While suppliers want to display products on shelves as much as possible, retailers want to maximize options for customer satisfaction; in agreements negotiated between the two sides, they set a minimum space for each product category. Since Migros has fixed each department's height, a display's length becomes the important variable. In our model, we did not initially change the current department dimensions; at the second stage of the problem, however, we consider increasing or decreasing a department's length by based on revenue per category per meter.

2. Adjacencies among departments

In a grocery store, displaying complementary products close to each other increases the possibility of impulse purchase and also provides a comfortable shopping experience. For this reason, we consider the adjacencies between departments. Needing a closeness assessment in our model, we used association rule mining, a data-mining technique used to identify relationships among groups of products, items or categories, to look both data from a store manager's experience and market basket data taken from the Migros Capitol store. This information helped to develop an adjacency matrix, subsequently inserted to optimize the layout.

Chapter 4

Simulation

This chapter presents the simulation of the grocery store layout problem; simulation supports the decision process of layout design and allows system evaluation over time. We used data from Migros and SIMIO software to simulate the current system and current layout; this will serve as a baseline for comparing candidate layouts with the existing one. Impulse purchase rates of each department in the store are considered during the simulation. Finally, the simulation model is validated by using ANOVA tests and comparing with the store actual data.

4.1. Simulation Modelling

"A model is a representation of the construction and working of some system of interest" (Maria, 1997). Modeling helps to understand the behavior of the system and to predict the effects of changes in the system. "A good model is a tradeoff between realism and simplicity" (Maria, 1997). If used before making change to an existing system, or building a new system, simulation can reduce the chances of failure to meet specifications and can help select parameters to optimize system performance.

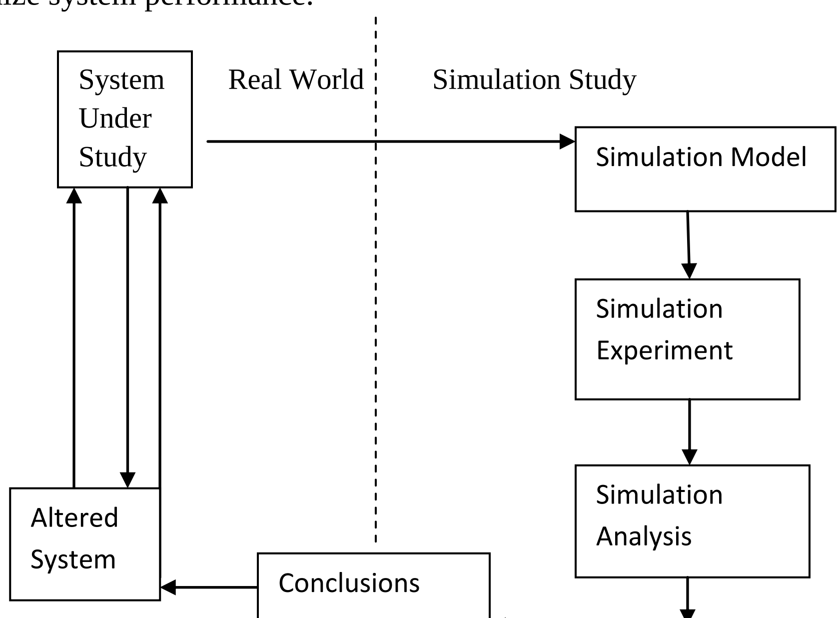

Figure 4.1: Simulation Study Schematic (Source: Maria, 1997)

“It is widely accepted that simulation is an integral part of any effective facility planning or layout study” (Aleisa and Lin, 2005). When used to study the behavior of manufacturing systems, simulation allows a good understanding of potential problems (Shahin and Poormostafa, 2011). Similarly, studying consumers’ in store behavior also serves as an important topic for academic researchers and industry practitioners. This project focuses on improving the layout of a grocery store and analysing consumers’ stochastic behaviour; simulation accurately represents these systems and creates different scenarios to analyze and evaluate system performance.

4.2. Grocery Store Simulation

Retail stores face challenging problems; the most significant of which involve the analysis of the store layout and allocation of optimal space for each product category (Bruzzone and Longo, 2010); these problems have processes involving a number of stochastic variables such as customer spending forecasts, quantity purchased and customer routings through the store. “It is widely recognized that simulation is a very powerful methodology for supporting decision problems within those systems where high complexity, owing to the relationships linking the variables involved and the random nature of those variables, prohibits the use of analytical methods and models unless they are extremely simplified” (Bruzzone and Longo, 2010). As mentioned above, as retail store processes involve numerous stochastic variables, simulation efficiently takes into account the system behavior as whole and uses data collected in a real store environment to evaluate the system.

In our case study, store data came from the Capitol Migros store in Istanbul, Turkey, a middle sized grocery store (1200 square meter 2M) located in a shopping mall with eight straight aisles, a racetrack aisle, one entrance and one exit; the actual layout appears in Figure 4.2. Twenty-nine departments include magazines and books, seasonal non-food, oil and spices, detergent, cleaning products, paper products, toys, pet food, cosmetics, juices, fish, snacks and nuts, alcoholic drinks, dairy, bakery, frozen food in the racetrack aisles and in the middle of the store, deli and side dishes, meat, poultry, cheese and olives, organic fruits, fruits and vegetables. In the inside aisles, from left to right, one finds soft drinks, coffee and tea, chocolate and cookies, beans and lentils, household, pet food, textile and shoes, and electronics.

The company's financial department collects revenue data in 25 categories; "household revenue" includes seasonal non-food, "oil and spices" includes beans and lentils, "soft drinks" includes juices, and the" pet food" and "toys" departments appear as one department. In conclusion, we have 25 departments' revenue data from the store to inform in our simulation model.

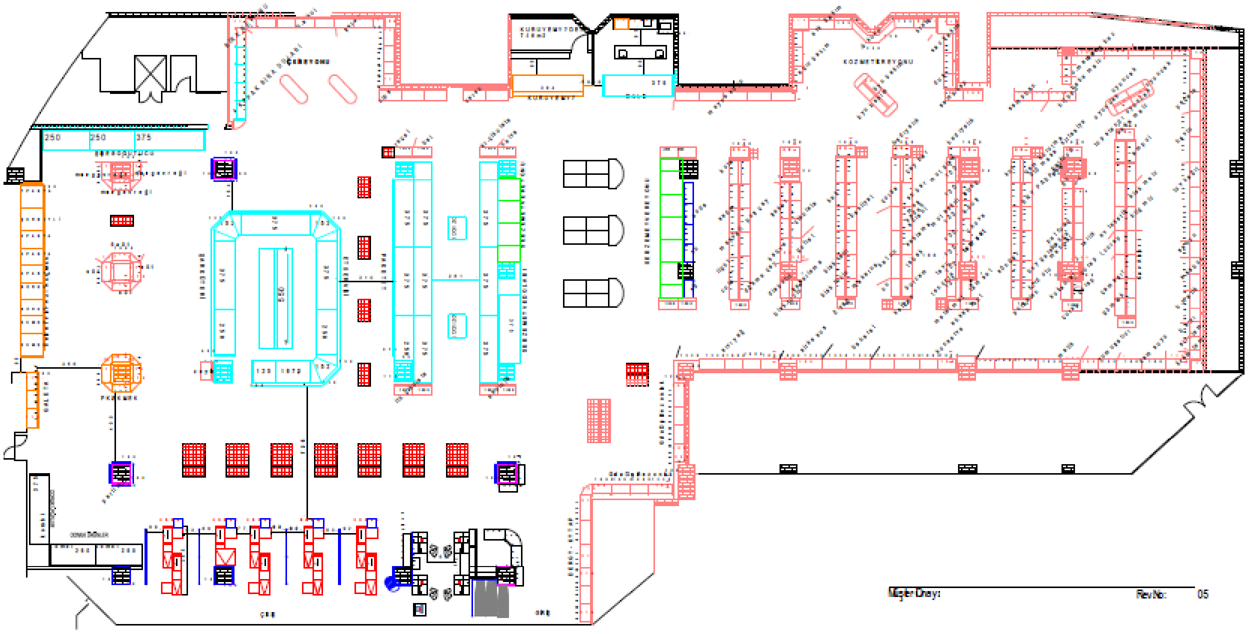

Figure 4.2: The Migros Capitol Store Layout

From the results of interviews with the store manager and from the observations in store, we made the following assumptions relating to the store:

- Customers fit in one of three categories- rush customers, customers with a cart and customers with a basket.
- Almost all shoppers enter the store with a shopping list either written or in their mind.
- Customers use the shortest path while routing in the store according to their shopping list.

It is important to remind that simulation results would change if these assumptions are modified. For instance, instead of employing the shortest path, Hui et al., (2012) assume shoppers use a "one step look ahead (1SLA)" algorithm at a time and measure the length of that path during shopping.

The simulation starts with the arrival of customers to the grocery store. According to the items in their shopping list, customers can either pick up a shopping cart or a basket or if in a hurry, pick up nothing in which to carry the items purchased. Then, by using a shortest path algorithm, the customer walks around the store and picks up the items on the list. When done, customer pays and leaves the store.

The steps of the simulation are as follows:

> *Problem definition:* The objective of the simulation model involves evaluating a candidate layout by estimating the total revenue of the current system and each department; and
>
> *Data collection:* According to the data directly taken from the store for a one year period, customers arrive at the store according to the following frequency:

	WEEKEND	**WEEKDAY**	**AVERAGE (customers/hr)**
09:00 AM	5	2	2.9
10:00 AM	174	163	166.1
11:00 AM	218	173	185.9
12:00PM	290	312	305.7
13:00PM	365	393	385.0
14:00PM	337	305	314.1
15:00PM	406	324	347.4
16:00PM	387	375	378.4
17:00PM	396	416	410.3
18:00PM	451	383	402.4
19:00PM	362	297	315.6
20:00PM	339	258	281.1
21:00PM	336	208	244.6
22:00PM	19	21	20.4

Table 4.1: Average daily number of customers per hour for Capitol Migros over a one year time period.

The store opens at 9 AM and closes at 10 PM. According to observations in the store and the interview with the store manager, the appropriate arrival rate for each type of customer is set 20% with cart, 20% with basket and 60% rush. Since Capitol Migros Store exists in a shopping mall, most of the customers rush through without either a cart or basket. The number of items purchased serves as the main distraction among the categories. The store averages daily total revenue on a weekday of 106,675TL and 139,955 TL on a weekend. Knowing the amount of money purchased from each department, we calculated the unit revenue for each department- the average amount a customer spends per visit.

PRODUCT CATEGORY	**SPENT (TL)**
ALCOHOLIC DRINKS and TOBACCO	(1, 2.94, 20)
BAKERY	(1, 1.43, 8)
BOOKS and MAGAZINES	(1, 1.51, 12)
CHEESE OLIVES	(2, 2.40, 23)
CHOCOLATE and COOKIES	(2.08, 2.67, 20)
CLEANING PRODUCTS	(0.5, 1.00, 7)
COSMETICS	(1, 2.08, 15)
DAIRY MILK YOGURT	(1, 1.65, 6)
DELI/SIDE DISH	(1, 1.31, 17)
DETERGENT	(1, 1.12, 10)
ELECTRONICS	(1, 2.00, 4)
FISH	(1, 1.46, 4)
FROZEN FOOD and EGG	(0.5, 1.00, 7)
FRUIT and VEGETABLES	(1, 2.05, 19)
HOUSEHOLD (seasonal nonfood)	(0.5, 0.81, 5)
MEAT SECTION	(1, 1.82, 12)
OIL and SPICES (lentils and beans)	(1, 1.16, 15)
ORGANIC FRUIT and VEGETABLES	(1, 1.60, 6)
PAPER PRODUCTS	(1, 1.49, 9)
POULTRY	(1, 1.68, 12)
SNACKSNUTS	(0, 0.70, 9)
SOFT DRINKS (juices)	(1, 1.18, 8)
TEA SUGAR BREAKFAST	(1, 1.93, 15)
TEXTILE and SHOES	(1, 1.50, 4)
TOYS and PET	(0, 0.23, 4)

Table 4.2 Triangular distributions for revenue per each department per customer for Capitol Migros used in the simulation.

We have limited data, but since we know the average value, we decided to use triangular distributions. A triangular distribution can model non-symmetric distributions but requires a minimum of actual data and shape assumptions. Therefore, it was an obvious choice for our simulation model. The sales for each department appears as a triangular distribution and has three values -pessimistic, most likely and optimistic. Data from an annual period was analyzed and, according to the amount purchased by the customers and the price of the item, optimistic and pessimistic values are selected for each department. See the Table 4.2. Each department appears on a customer's shopping list according to a triangular distribution. The data to support these distributions comes from the percentage of quantity sold to customers on a daily basis.

DEPARTMENT	**VISIT PROBABILITY**
ALCOHOLIC DRINKS and TOBACCO	(0, 0.042, 0.15)
BAKERY	(0, 0.1, 1)
BOOKS and MAGAZINES	(0, 0.02, 0.1)
CHEESE OLIVES	(0, 0.035, 0.1)
CHOCOLATE and COOKIES	(0, 0.20, 1)
CLEANING PRODUCTS	(0, 0.008, 0.02)
COSMETICS	(0, 0.04, 0.1)
DAIRY MILK YOGURT	(0, 0.09, 0.5)
DELI/SIDE DISH	(0, 0.015, 0.1)
DETERGENT	(0, 0.021, 0.1)
ELECTRONICS	(0, 0.004, 0.1)
FISH	(0, 0.003, 0.5)
FROZEN FOOD and EGG	(0, 0.02, 0.5)
FRUIT and VEGETABLES	(0, 0.11, 0.5)
HOUSEHOLD (seasonal nonfood)	(0, 0.02, 0.1)
MEAT SECTION	(0, 0.008, 0.5)
OIL and SPICES (lentils and beans)	(0, 0.03, 0.5)
ORGANIC FRUIT and VEGETABLES	(0, 0.012, 0.5)
PAPER PRODUCTS	(0, 0.025, 0.2)
POULTRY	(0, 0.008, 0.5)
SNACKSNUTS	(0, 0.004, 0.01)
SOFT DRINKS (juices)	(0, 0.11, 1)
TEA SUGAR CANNED FOOD BREAKFAST	(0, 0.07, 0.3)
TEXTILE and SHOES	(0, 0.003, 0.01)
TOYS and PET	(0, 0.005, 0.01)

Table 4.3: Triangular distributions of visit probability of each department for Capitol Migros

When a customer enters the store, the simulation dynamically creates a shopping list by considering the visit probabilities given above and routes the customers by shortest path. The customer picks up the items, spends money in that department according to the triangular distribution given in Table 4.2, and leaves the store at the only exit. At the end the of simulation run, the total revenue is calculated, the total number of customers visiting the store is seen, and average money spent for each department is calculated. To validate the simulation, the total revenue value is compared for 2400 hours (100 days) run of the simulation model with the original data. One hundred days was chosen as the simulation period because we had one year total of data and, considering possible seasonal factors, this time period is a reasonable choice. The total average revenue per day is 108,471.08 TL. The results for each department are given below:

PRODUCT CATEGORY	STORE VALUE	SIMULATION
ALCOHOLIC DRINKS and TOBACCO	13,165.77	12,418.53
BAKERY	5,629.22	4,352.10
BOOKS and MAGAZINES	2,164.40	1,581.91
CHEESE OLIVES	9,500.07	8,849.02
CHOCOLATE and COOKIES	10,793.50	10,105.92
CLEANING PRODUCTS	1,606.84	1,477.69
COSMETICS	7,329.55	6,687.72
DAIRY MILK YOGURT	6,193.63	5,043.10
DELI/SIDE DISH	5,188.10	4,808.06
DETERGENT	4,602.05	3,653.05
ELECTRONICS	2,075.26	1,998.08
FISH	2,120.22	1,677.83
FROZEN FOOD and EGG	3,113.27	3,152.64
FRUIT and VEGETABLES	7,752.43	7,093.12
HOUSEHOLD (season nonfood)	3,323.67	3,070.65
MEAT SECTION	6,734.24	6,243.20
OIL and SPICES (beans and lentils)	4,307.47	3,784.46
ORGANIC FRUIT and VEGETABLES	2,173.00	2,138.48
PAPER PRODUCTS	5,863.68	5,082.78
POULTRY	2,518.21	2,219.13
SNACKSNUTS	2,660.95	2,244.60
SOFT DRINKS (juices)	4,108.07	3,186.76
TEA CANNED FOOD SUGAR BREAKFAST	7,481.34	6,566.00
TEXTILE and SHOES	644.42	400.00
TOYS and PET	923.00	832.27
	121,972.31	**108,667.10**

Table 4.4: Comparison of Simulation Results with Migros data over 2400 hours

The simulation results, without impulse purchases, only consider customers buying from their shopping lists; in practice, product displays may influence consumers during shopping, and they may buy extra. So the store values exceed simulation results.

4.3. The Simulation Software: SIMIO

Most simulation studies use simulation software packages; hundreds of simulation products have appeared on the market, many with price tags of $15,000 or more. How to select the best simulation software for our model? “Metrics for evaluation include modeling flexibility, ease of use, modeling structure (hierarchical v/s flat; object-oriented v/s nested), code reusability, graphic user interface, animation, dynamic business graphics, hardware and software requirements, statistical capabilities, output reports and graphical plots, customer support, and documentation”(Maria, 1997).

SIMIO, a simulation tool developed in 2007, represents a new approach in simulation object orientation; modeling is based on describing interaction of the objects. SIMIO supports the following (Pavel et al., 2010):

- Creating 3D animation by one step importing and 3D objects from Google 3D Warehouse;
- Importing data from Excel worksheets; and
- Writing logic functions, such as priority rules, in many languages, including C++ and Visual Basic.

The Migros Capitol store layout, assembled in SIMIO, appears in the following figure.

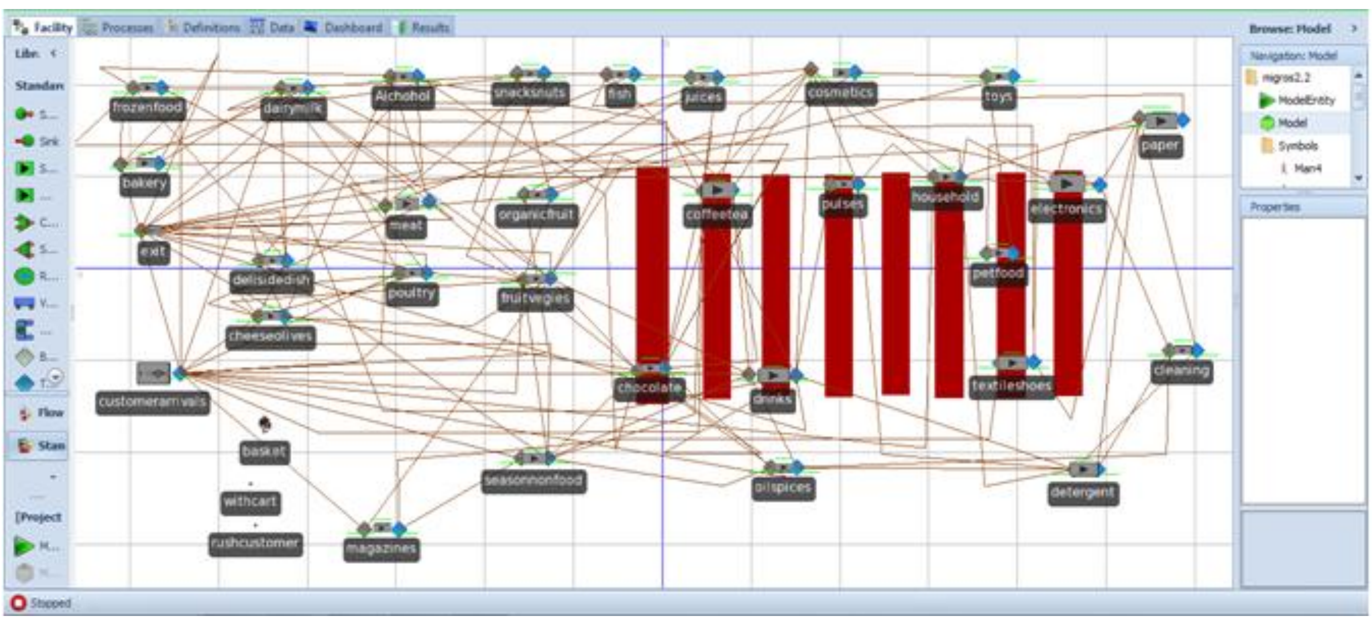

Figure 4.3: SIMIO representation of the Migros Capitol layout

The inter-arrival rates entered for weekends and weekdays appear below:

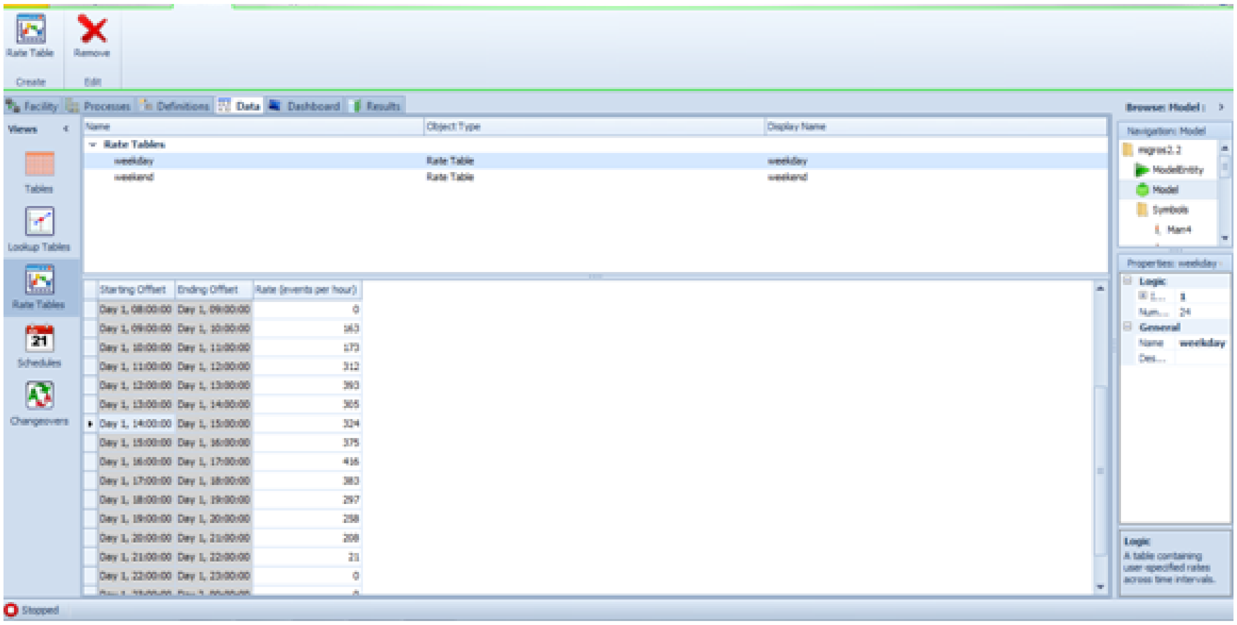

Figure 4.4: Inter arrival times per hour per day in SIMIO

We generated three customer categories.

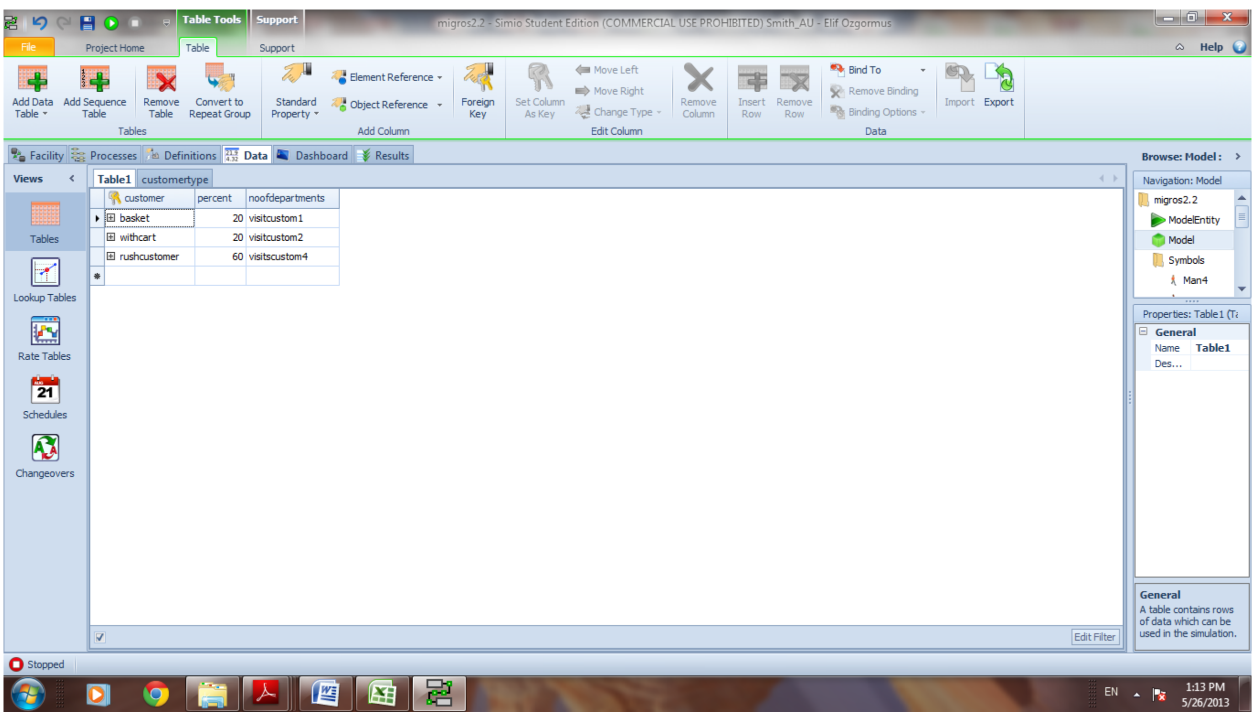

Figure 4.5: Types of customers in Migros represented in a SIMIO table

For each department, we entered the visit probabilities (used to create shopping lists) to a table as distribution values.

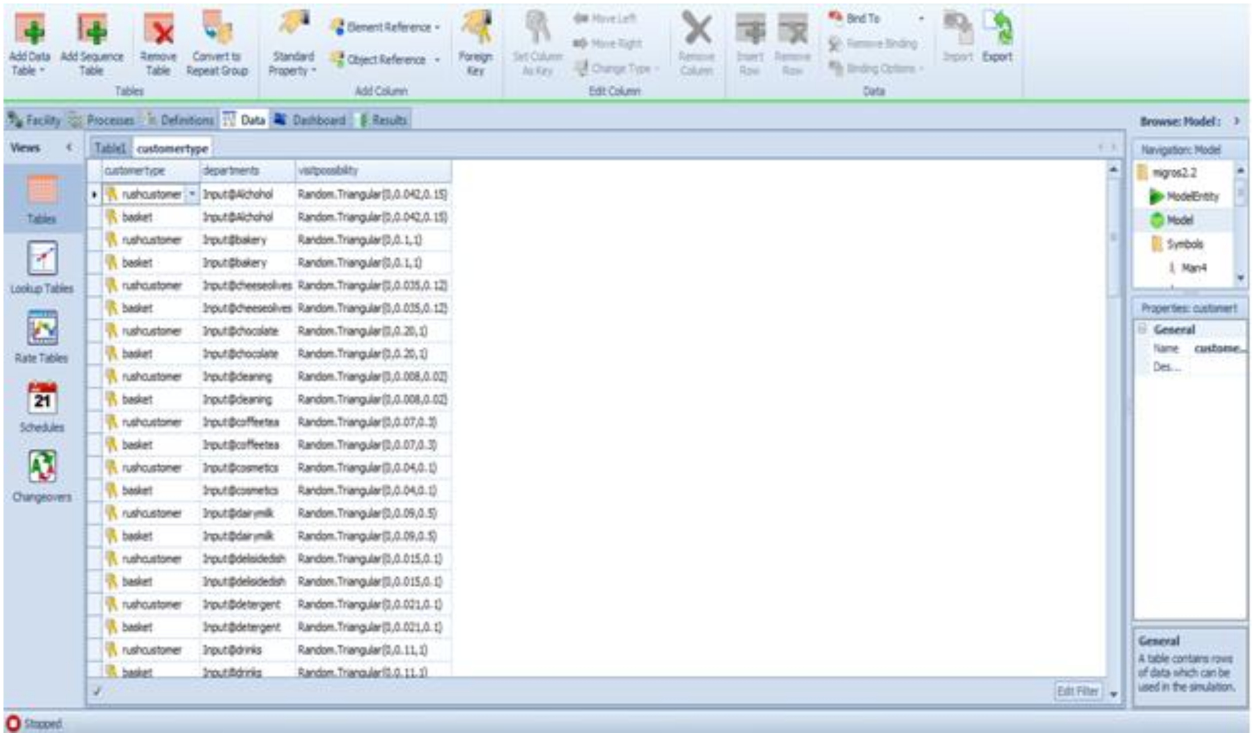

Figure 4.6: Visit probability for each type of customer per each day in Migros represented in SIMIO

For the calculation of revenue for each department, we defined the revenue distributions per visit as given in Table 4.2.

A 3D view in SIMIO makes the model view more realistic.

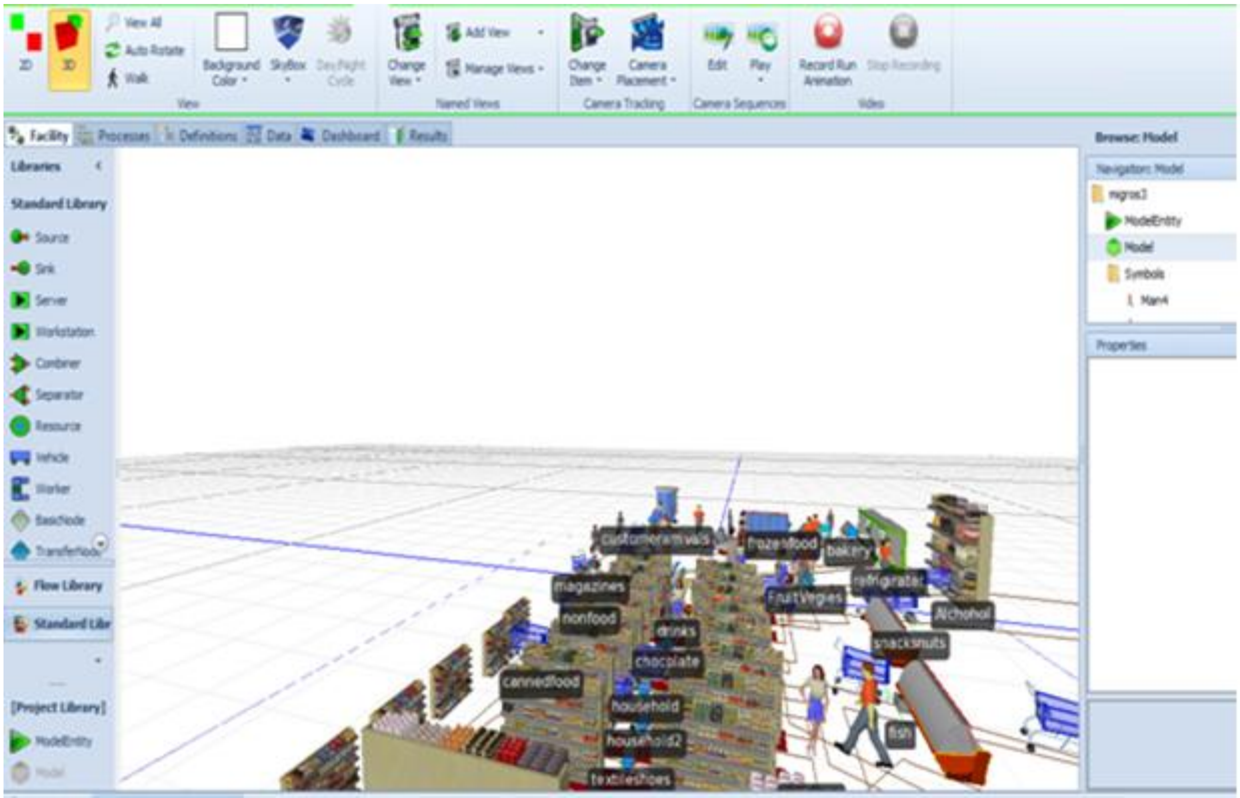

Figure 4.7: Migros Capitol represented in a 3D view in SIMIO

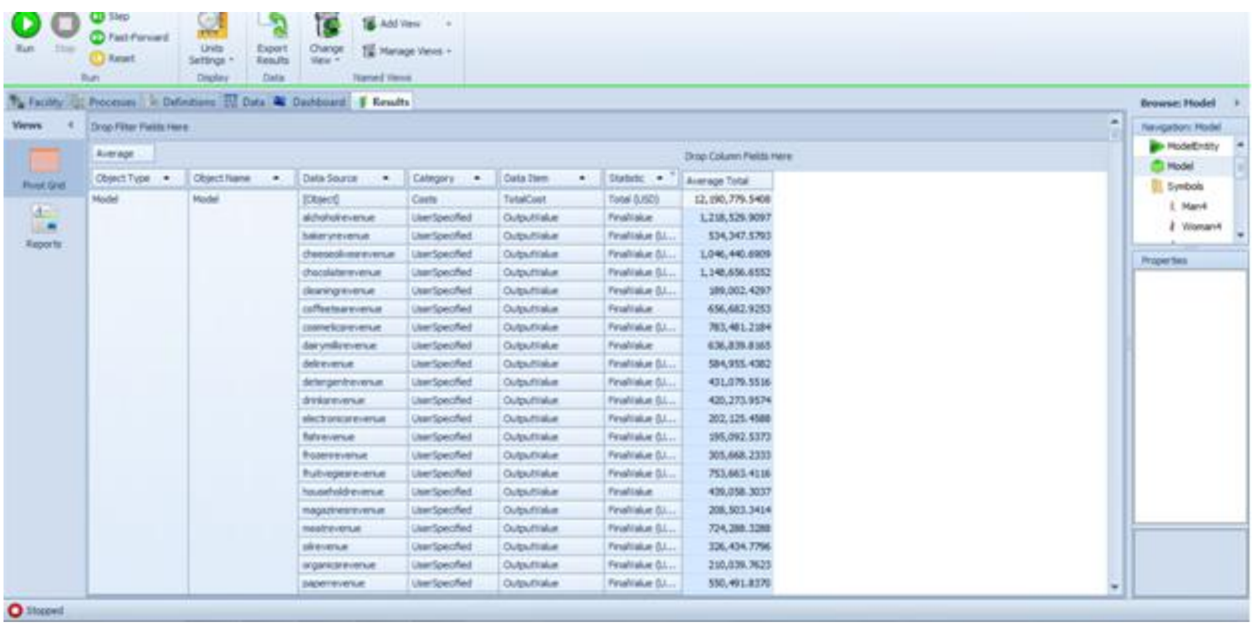

Figure 4.8: Revenue results in SIMIO

Finally, we checked the results of simulated system and compared with the original system as shown in the previous section.

4.4. Refined Model

After the initial simulation of the current layout, we focused on how to make our virtual grocery store more realistic. We consider impulse purchase rates and calculate the extra impulse purchases since we want to improve the grocery store layout to increase the total revenue. We will propose two ways to increase the total revenue-increasing impulse purchase rates and optimizing each department's area based on unit revenue.

4.4.1. Impulse Purchase Model 1

Every product category has a different impulse purchase rate directly affects the customer behavior. Even though some items do not appear in a customer's shopping list, as the customer passes by that department, the product's impulse rate category determines the likelihood the shopper will stop and make an extra purchase. We can illustrate the model with a small, six department grocery store.

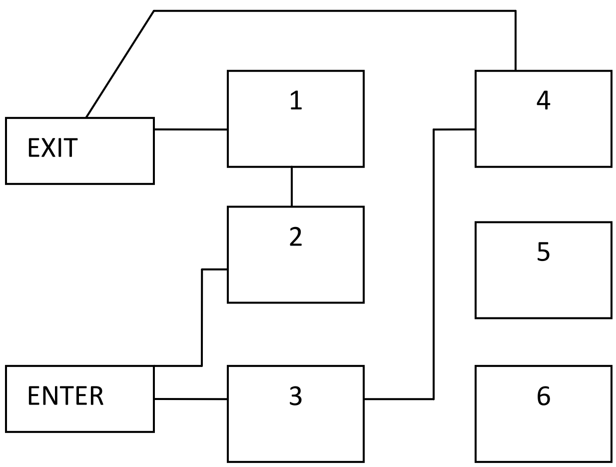

Figure 4.9: Routing Logic

For the refined model, we had an interview with the store manager and asked him to define the impulse purchase rates of the 25 product categories using his considerable experience. We used the impulse buying tendency scale (Verplanken and Herabadi, 2001), a 5-point Likert-type scale ranging from 1 (very low) to 5 (very high).Then we assigned a probabilistic triangular distribution extra spent amount for each impulse purchase rating, calculated by considering the average spent amount per customer. In this Migros store, a customer spends on average 30TL and it is assumed that the impulse purchase amount is a maximum of 20% of the customer's regular budget (In the research paper, "Unplanned Category Purchase Incidence: Who Does It, How Often and Why," Bell et al.,2009 argue that the amount of unplanned buying is close to 20%) . With a departmental impulse rate of 1, the customer may not spend any extra, most likely will spent 1 more TL and maximum of 2 TL. With an impulse rate of 2, the customer may not spend any extra, most likely will spend 2 TL and will not exceed a maximum spent of 3 TL.

Impulse Rate	**Triangular distribution of extra spent (TL)**
1	(0, 1, 2)
2	(0, 2, 3)
3	(1, 2, 3)
4	(1, 3, 5)
5	(2, 4, 6)

Table 4.5 Impulse purchase rates and extra spent amount in TL for small grocery store

The impulse rates of these departments are assigned 5, 4, 3, 1, 1, and 2 respectively. The significant point in this model, the routing of the customers, shows departments' locations guide the customer's route. For instance, the customer initially has a shopping list with two items; she will go department 2, then 1 and exit, with the routing following a shortest path algorithm. SIMIO uses the actual physical length to calculate the shortest path. In this case, with an impulse rate for department 3 of 3, the customer will pass by department. If the department's impulse rate exceeds 1, the customer may possibly spend extra in department 3. With a customer's shopping list composed of departments 3 and 4, the route of the customer covers all aisles, but with department 5 having an impulse rate of 1, the customer might stop by departments 2 and 1, and spent extra. Triangular distributions represent the impulse sales for each department as explained above. We used this algorithm, modeled in SIMIO, with a hypothetical six-department store, before applying it to the whole grocery store -25 departments. The current system is generated as explained above.

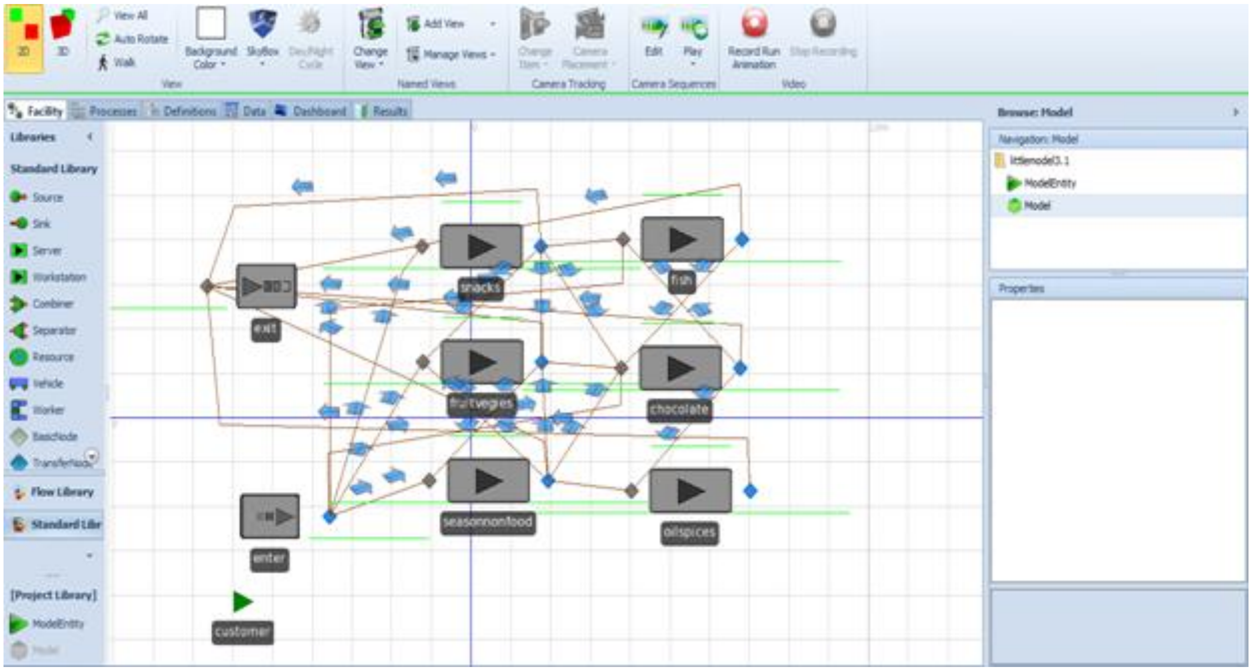

Figure 4.10: Small grocery store example of impulse buying.

The total revenue and revenues per department per day without the impulse purchase are as follows:

Total revenue: 39,390.8TL

Department No	Department Name	Revenue(TL)
1	Snack and Nuts	1,623.4
2	Fruit and Vegetables	13,291.2
3	Seasonal-non food	2,376.6
4	Fish	2,805.5
5	Chocolate	14,341.3
6	Oil and spices	4,952.5

Table 4.6 Departments of small grocery store and total revenue per day per each department

SIMIO creates a search table, checking the impulse rate assigned value each time a customer passes a department, and, according to scale and probabilities, deciding if the customer will buy extra.

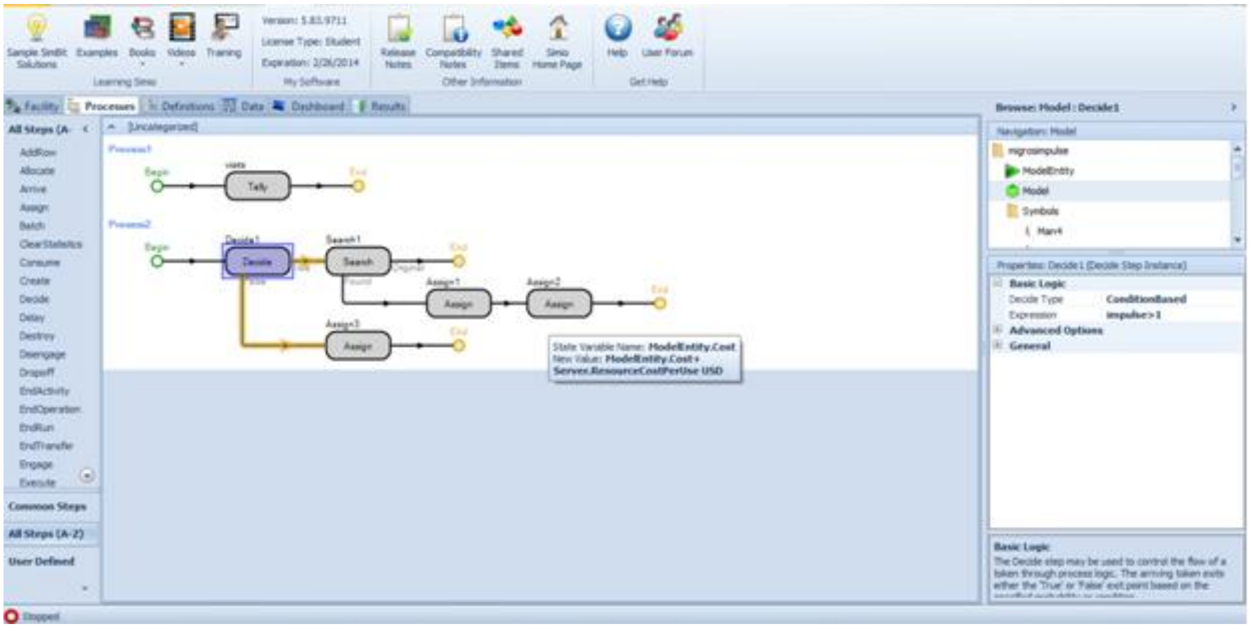

Figure 4.11: Small grocery store process logic in SIMIO

In SIMIO, node lists represent the routing explained above. Every department has an aisle; for instance, department 1 has an aisle composed of neighboring nodes with a possibility to stop by according to impulse purchase rate. So, the customer could enter department 2, 3 and 4 and exit. Then from this node list, randomly choose a node to enter. If the chosen node has an impulse rate greater than 1, the customer enters this department and according to the distribution of extra spent, makes an additional purchase. The exit node always appears in the node list since the customer could immediately finish shopping and leave the store.

Department No	**Department Name**	**Revenue(TL)**
1	Snack and Nuts	1,931.6
2	Fruit and Vegetables	13,291.2
3	Seasonal-non food	2,364.1
4	Fish	3,156.1
5	Chocolate	15,633.9
6	Oil and spices	5,837.1

Table 4.7 Total revenue including impulse purchases per day per each department

The new total revenue is 42,482.2TL and revenues per department with impulse purchase are given in Table 4.7.

As seen from the results of six department store, considering properly impulse purchases increases the revenue of the store.

4.4.2. Migros Simulation Results

By using impulse purchase rates, we regenerated the model as explained above for the Migros original data; we defined the impulse purchase rates on a scale of 1 to 5, resulting from the interview with the store manager, Fuat Sahin.

PRODUCT CATEGORY	IMPULSE RATE
ALCOHOLIC DRINKS and TOBACCO	3
BAKERY	5
BOOKS and MAGAZINES	3
CHEESE OLIVES	3
CHOCOLATE and COOKIES	5
CLEANING PRODUCTS	2
COSMETICS	5
DAIRY MILK YOGURT	4
DELI/SIDE DISH	4
DETERGENT	2
ELECTRONICS	1
FISH	3
FROZEN FOOD and EGG	1
FRUITS and VEGETABLES	4
HOUSEHOLD	2
MEAT SECTION	2
OIL and SPICES	4
ORGANIC FRUIT and VEGETABLES	1
PAPER PRODUCTS	2
POULTRY	2
SNACKNUTS	4
SOFT DRINKS	3
TEA SUGAR CANNED FOOD BREAKFAST	4
TEXTILE and SHOES	3
TOYS and PET	1

Table 4.8 Impulse purchase rates of product categories assumed in the refined model.

Impulse rate	Triangular distribution of extra spent (TL)
1	(0, 1, 1)
2	(1, 1, 2)
3	(1, 2, 3)
4	(1, 3, 5)
5	(2, 4, 6)

Table 4.9 Impulse purchase rates and extra spent amount in TL for Migros Store

The new revenue is calculated as 121,757.4 TL.

PRODUCT CATEGORY	STORE VALUE	ORIGINAL SIMULATION	REFINED SIMULATION
ALCOHOLIC DRINKS and TOBACCO	13,165.77	12,418.53	12,894.77
BAKERY	5,629.22	4,352.10	5,788.87
BOOKS and MAGAZINES	2,164.40	1,581.91	2,404.88
CHEESE OLIVES	9,500.07	8,849.02	9,301.20
CHOCOLATE and COOKIES	10,793.50	10,105.92	10,785.56
CLEANING PRODUCTS	1,606.84	1,477.69	1,690.86
COSMETICS	7,329.55	6,687.72	8,268.58
DAIRY MILK YOGURT	6,193.63	5,043.10	5,479.30
DELI/SIDE DISH	5,188.10	4,808.06	5,765.82
DETERGENT	4,602.05	3,653.05	4,395.20
ELECTRONICS	2,075.26	1,998.08	2,023.36
FISH	2,120.22	1,677.83	1,992.56
FROZEN FOOD and EGG	3,113.27	3,152.64	3,085.40
FRUIT and VEGETABLES	7,752.43	7,093.12	7,879.47
HOUSEHOLD (season nonfood)	3,323.67	3,070.65	3,131.60
MEAT SECTION	6,734.24	6,243.20	6,296.44
OIL and SPICES (beans and lentils)	4,307.47	3,784.46	3,848.61
ORGANIC FRUIT and VEGETABLES	2,173.00	2,138.48	2,256.44
PAPER PRODUCTS	5,863.68	5,082.78	5,721.83
POULTRY	2,518.21	2,219.13	2,887.61
SNACKSNUTS	2,660.95	2,244.60	3,047.11
SOFT DRINKS (juices)	4,108.07	3,186.76	3,730.28
TEA CANNED FOOD SUGAR BREAKFAST	7,481.34	6,566.00	7,241.69
TEXTILE and SHOES	644.42	400.00	594.02
TOYS and PET	923.00	832.27	1,245.55
	121,972.31	**108,667.10**	**121,757.00**

Table 4.10: The comparison of real store data with the refined simulation results

When we look at the simulation results in detail, we can make some useful analyses. The real system's total revenue of 122,000 TL/day nearly matches the simulation's results after using the impulse rates set by the store's manager. Two departments having higher extra revenue than the others, bakery and cosmetics, also have high impulse rates, leading one to expect a direct relationship, but both deli and fruit and vegetables have slightly lower impulse rates and still have higher revenues. Apparently, these departments' locations promote impulse purchases; their high traffic zones give them extra visibility for purchases. If high impulse purchase-rated products are located in a hot zone, the extra spent amount increases significantly, and, in the same way, if we locate the high impulse -rated product categories in low traffic areas, this will negatively influence the extra spent amount. We can see an example of the location effect in our model with the books and magazines department; although it has an impulse purchase rate of 3, because of it is located next to the entrance to the store, the daily revenue amount increased a lot.

4.4.3. Final Model

In the previous impulse purchase model, we used a scale of 1 to 5 for all 25 departments and assigned the same amount of money for extra spent. Each department has different unit revenue and different purchased amounts, however, so it makes more sense to consider different impulse purchase distributions in the model. As we mentioned earlier, Bell et al. (2009), studied grocery shoppers' behaviors in the Netherlands and stated that 18% of the purchased amount in the shopping basket are unplanned. It is also stated in the paper that the impulse purchase level significantly affects the spent amount. In the light of these observations, we generated a simple formula: Knowing the average purchased amount per each department, the customer most likely will spend is assumed that the customer might most likely to spend 10 percent of this amount times impulse rate even though it is not in her/his shopping list. For instance, average purchased amount for alcoholic drinks and tobacco is 2.94TL and an impulse rate of 3, the extra spent amount for this department would total 3*2.94*0.10=0.88TL. Using a triangular distribution for example for the alcohol department, the extra spent amount would appear as (0.2, 0.88, 2) TL. The minimum and maximum values are assigned by considering the average spent amount. Table 4.11 gives the impulse rates and extra spent amount distributions for each department.

PRODUCT CATEGORY	impulse rate	avg purchased (TL)	most likely (TL)	expected extra spent distribution
ALCOHOLIC DRINKS and TOBACCO	3	2.94	0.88	Random.Triangular(0.2,0.88,2)
BAKERY	5	1.43	0.72	Random.Triangular(0.1,0.72,1.5)
BOOKS and MAGAZINES	3	0.51	0.15	Random.Triangular(0.1,0.15,0.5)
CHEESE OLIVES	3	2.38	0.71	Random.Triangular(0.2,0.71,2)
CHOCOLATE and COOKIES	5	2.67	1.34	Random.Triangular(1,1.34,4)
CLEANING PRODUCTS	2	0.41	0.08	Random.Triangular(0.1,0.2,1)
COSMETICS	5	2.08	1.04	Random.Triangular(0.3,1.00,1.5)
DAIRY MILK YOGURT	4	1.65	0.66	Random.Triangular(0.2,0.3,1.3)
DELI/SIDE DISH	4	1.31	0.52	Random.Triangular(0.3,0.52,5)
DETERGENT	2	1.12	0.22	Random.Triangular(0.1,0.22,0.5)
ELECTRONICS	1	0.44	0.04	Random.Triangular(0.01,0.04,1)
FISH	3	0.46	0.14	Random.Triangular(0.1,0.14,1)
FROZEN FOOD and EGG	1	0.77	0.08	Random.Triangular(0.01,0.08,0.7)
FRUIT and VEGETABLES	4	2.05	0.82	Random.Triangular(0.5,0.82,1.5)
HOUSEHOLD (season nonfood)	2	0.81	0.16	Random.Triangular(0.1,0.16,0.5)
MEAT SECTION	2	1.82	0.36	Random.Triangular(0.1,0.36,1)
OIL and SPICES (beans and lentils)	4	1.16	0.46	Random.Triangular(0.2,0.46,2.5)
ORGANIC FRUIT and VEGETABLES	1	0.60	0.06	Random.Triangular(0.01,0.06,0.1)
PAPER PRODUCTS	2	1.49	0.30	Random.Triangular(0.1,0.3,0.4)
POULTRY	2	0.68	0.14	Random.Triangular(0.05,0.14,0.5)
SNACKSNUTS	4	0.83	0.33	Random.Triangular(0.1,0.33,1.5)
SOFT DRINKS (juices)	3	0.83	0.25	Random.Triangular(0.1,0.25,0.8)
TEA CANNED FOOD SUGAR BREAK	4	1.18	0.47	Random.Triangular(0.2,0.47,1.5)
TEXTILE and SHOES	3	1.93	0.58	Random.Triangular(0.1,0.58,1.5)
TOYS and PET	1	0.13	0.01	Random.Triangular(0,0.01,0.5)

Table 4.11 Impulse rates of departments with average purchased amount and expected extra spent amount.

This table is inserted into SIMIO model as shown in Figure 4.12. In the middle column there is “compare” value. Whenever customer visits a department, a random number is generated between 0 and 1. This number is compared with the value in the table. The compare value is determined according to the rate of impulse purchase and these are shown in Table 4.12. For instance there is a compare value of 0.1 for an impulse rate of 1 and a value of 0.8 for impulse rate 5. Actually, compare value represents the possibility of impulse purchase. As high impulse purchase rated product categories have high possibility, these values are assigned. If the compare value exceeds the random number generated, the customer makes an extra purchase amount and this amount is according to the triangular distribution as defined in each row. Otherwise, the customer spends no extra money in that department.

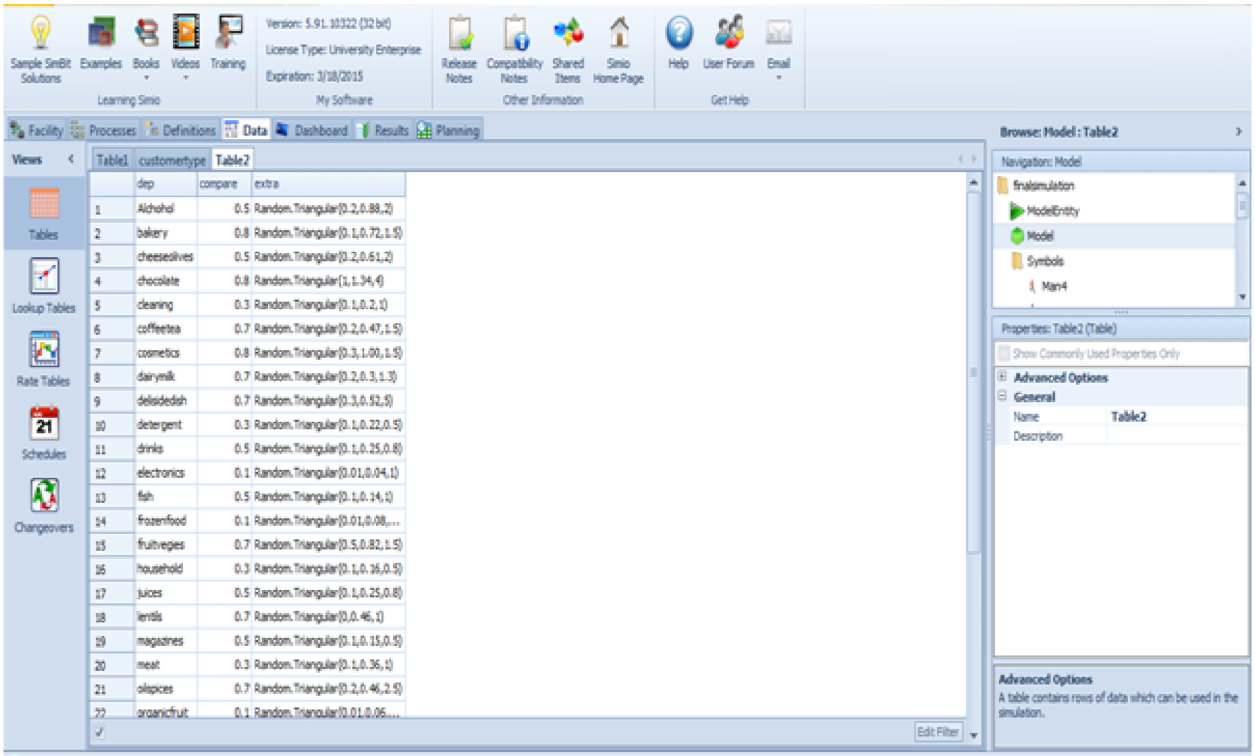

Figure 4.12.Extra spent amounts per each department in SIMIO Model.

impulse rate	compare value
1	0.1
2	0.3
3	0.5
4	0.7
5	0.8

Table 4.12 Compare values for simulation

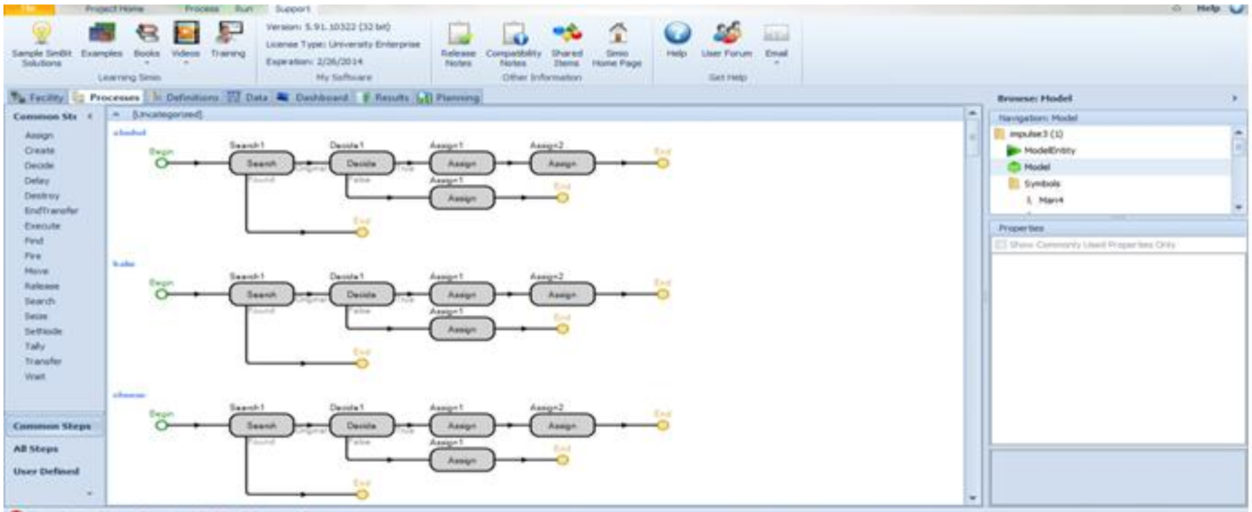

Figure 4.13 Process Logic for Model Impulse Purchase 2

This process is inserted to SIMIO by using the Search, Decide, and Assign Steps. Figure 4.13 shows the process for the alcohol, bakery and cheese departments. For instance, whenever the customer walks by any department, a random number is generated. The Search Step looks for the compare value of that particular department. Then the Decide step is used to compare the random number and the compare value of that department. If the compared value is greater than the random number, the Assign step goes to the row of the extra spent amount and assigns the value by considering the triangular distribution using another random variable. No extra spent is assigned if the random number generated is more than the compare value.

PRODUCT CATEGORY	STORE VALUE	ORIGINAL SIMULATION	REFINED SIMULATION	FINAL SIMULATION
ALCOHOLIC DRINKS and TOBACCO	13,165.77	12,418.53	12,894.77	13,074.94
BAKERY	5,629.22	4,352.10	5,788.87	5,511.91
BOOKS and MAGAZINES	2,164.40	1,581.91	2,404.88	2,146.86
CHEESE OLIVES	9,500.07	8,849.02	9,301.20	9,485.10
CHOCOLATE and COOKIES	10,793.50	10,105.92	10,785.56	10,772.28
CLEANING PRODUCTS	1,606.84	1,477.69	1,690.86	1,655.57
COSMETICS	7,329.55	6,687.72	8,268.58	7,512.22
DAIRY MILK YOGURT	6,193.63	5,043.10	5,479.30	6,272.31
DELI/SIDE DISH	5,188.10	4,808.06	5,765.82	5,191.20
DETERGENT	4,602.05	3,653.05	4,395.20	4,682.28
ELECTRONICS	2,075.26	1,998.08	2,023.36	2,074.68
FISH	2,120.22	1,677.83	1,992.56	2,066.59
FROZEN FOOD and EGG	3,113.27	3,152.64	3,085.40	3,128.46
FRUIT and VEGETABLES	7,752.43	7,093.12	7,879.47	7,783.82
HOUSEHOLD (season nonfood)	3,323.67	3,070.65	3,131.60	3,383.79
MEAT SECTION	6,734.24	6,243.20	6,296.44	6,653.90
OIL and SPICES (beans and lentils)	4,307.47	3,784.46	3,848.61	4,229.97
ORGANIC FRUIT and VEGETABLES	2,173.00	2,138.48	2,256.44	2,192.54
PAPER PRODUCTS	5,863.68	5,082.78	5,721.83	5,859.18
POULTRY	2,518.21	2,219.13	2,887.61	2,594.55
SNACKSNUTS	2,660.95	2,244.60	3,047.11	2,664.02
SOFT DRINKS (juices)	4,108.07	3,186.76	3,730.28	4,011.28
TEA CANNED FOOD SUGAR BREAKFAST	7,481.34	6,566.00	7,241.69	7,492.80
TEXTILE and SHOES	644.42	400.00	594.02	674.47
TOYS and PET	923.00	832.27	1,245.55	874.49
	121,972.31	**108,667.10**	**121,757.00**	**121,989.20**

Table 4.13 The comparison of real store data with final simulation results

As seen from Table 4.13, the new results are almost same as real store data. The final simulation model considers both the probability of making impulse purchase and the extra spent amount specific for each department; these assumptions make the simulation more realistic.

Finally, for comparing the model to actual system behavior, validation is needed. It is utilized to determine if the model is an accurate representation of the real system. A one-way analysis of variance (ANOVA) is used to determine if there are any significant differences between the means of two or more independent groups. As seen from the results of the ANOVA test in Table 4.14, the Sig. value in the last column is greater than 0.05 in all tests. We can conclude that there is no statistically significant difference between store data and our simulation models at 95% confidence.

Store data versus original simulation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3540568.112	1	3540568.112	.369	.547
Within Groups	4.612E8	48	9607434.929		
Total	4.647E8	49			

Store data versus refined simulation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	927.099	1	927.099	.000	.992
Within Groups	4.812E8	48	1.003E7		
Total	4.812E8	49			

Store data versus final simulation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11301.208	1	11301.208	.001	.973
Within Groups	4.851E8	48	1.011E7		
Total	4.851E8	49			

Table 4.14: ANOVA test results of store data versus proposed simulations

As we mentioned earlier, this first stage of our project aims to characterize revenue using impulse rates, but we changed neither the size nor the location of any department; later, we will use heuristic optimization methods to consider these changes to improve total revenue while maintaining minimum area requirements.

Chapter 5

Market Basket Data Analysis

This chapter provides a deeper view of grocery store customer preferences and inter-relationships between product categories. We evaluated the market basket data collected from the MIGROS Capitol store to understand the consumer's decision- making process. The data is entered to MATLAB and analyzed by using association rule mining (also known as affinity analysis). From the findings of affinity analysis, we developed an adjacency matrix used in optimization stage.

5.1. Market Basket Data

In today's global world, knowledge is a power and retailers who are able to extract the knowledge hidden in data will gain competitive advantage in the market (Rygielski et. al., 2002) The exponential growth of computer networks and data-collection technology has increased capabilities to collect and store data of all kinds. "The tools and technologies of data warehousing, data mining, and other customer relationship management (CRM) techniques afford new opportunities for businesses to act on the concepts of relationship marketing" (Rygielski et. al., 2002). Since all mid to large scale retailers today possess electronic sales transaction systems, retailers are interested in analyzing these data to learn from consumer's behaviour (Brijs et al., 2000). "Data mining is an effective way to provide better service to customers and adjust offers according to their needs and motivations"(Gancheva, 2013).

"Market basket analysis, also known as association rule mining or affinity analysis, is a data-mining technique that originated in the field of marketing to identify relationships between groups of products, items, or categories, but recently has been used effectively in other fields, such as bioinformatics, nuclear science, pharmacoepidemiology,immunology, and geophysics."(Aguinis et al., 2013). "It discovers co-occurrence relationships among activities performed by (or recorded about) specific individuals or groups"(Eddla et. al., 2011). In retail enterprise analysis and modeling, affinity analysis is used to understand the purchase behavior of customers.

Grocery shopping trips involve multi-category decision making for consumers and such multi-category decision processes result in the formation of shopping or market baskets (Mild and Reutterer, 2003). “Market basket choice is a decision process in which a consumer selects items from a number of product categories on the same shopping trip” (Russell and Petersen, 2000). Retail organizations, especially supermarkets, can provide consumer transaction data with their loyalty cards or with electronic sales transaction systems. “This information can be used to determine the placement of products, designing sales promotions for different segments of customers, to improve customer satisfaction and hence the profit of the supermarket” (Annie and Kumar, 2012). By discovering association rules, marketing analysts try to find sets of products that are frequently bought together (Wang et al., 2004). They aim to extract interesting correlations, frequent patterns, associations among sets of items in the transaction databases (Chen, 2007). For instance, customers who buy shampoo often also buy several products related to shampoo like conditioner. Placing these groups side by side in a retail center allows customers to access them conveniently.

In the remaining of this study, the empirical data used is obtained from the Capitol Migros store. While each store is different, the methodology developed is general and should be applicable, with few modifications, to a wide range of grocery stores. To investigate the relationships among products, a randomly selected month of transactional data of the costumers was obtained and analyzed. The CRM department recommended to choose a month period because they also analysis the loyalty cards and promotions per each month. The data is a list of sales transactions, wherein each transaction has two dimensions, one dimension represents the main product category and the other represents a customer. The goal of the analysis is to find which products are sold together so that we can develop an adjacency matrix based on the actual sales behaviors characteristic of the store.

5.2. Association Rules

One of the most important objectives in data mining is the development of association rules from large databases. Association rule learning which was first introduced by Agrawal et al. and is a popular method for discovering interesting relations among variables in large databases. The purpose of conducting such a study is to discover the co-occurrence associations among data in large databases, i.e., to find items that imply the presence of other items in the same transaction. More specifically, the association rules specify the percentages of consumers that buy product A who also buy product B (Tan and Kumar, 2005).

Three standard measures generally used to understand the presence, nature, and strength of an association rule are lift, support, and confidence (Berry and Linoff, 2004; Zhang and Zhang, 2002). "First, lift value is obtained because it provides information on whether an association actually exists or not. If the value for lift suggests that an association rule exists, the next step is to obtain the value for support, which is the actual probability that a set of items co-occurs with another set of items in a data set. Then, confidence is computed, which is the probability that a set of items occurs given that another set of items has already occurred" (Aguinis et al., 2013).

"Lift serves a function similar to statistical significance testing in more traditional analyses and is defined as $\frac{P(A \cap B)}{P(A) * P(B)}$" (Aguinis et al., 2013).The denominator assumes that events A and B occur independently of each other but the numerator assumes that A and B co-occur, an assumption that is reflected in the probability of the union of the two events. Thus, a lift value greater than 1.0 indicates the presence of A is associated with the presence of B-a positive relationship (Aguinis et al., 2013).

"Support is defined as $P(A \cap B)$and it is the probability that A and B co-occur" (Aguinis et al., 2013). It denotes the frequency of the rule within transactions. A high value means that the rule involves a great part of database**.** A disadvantage of support is that its usefulness decreases in the presence of very large (e.g., containing millions of transactions) and rich (e.g., containing thousands of items) data sets (Cohen et al., 2001).

Confidence, defined as $\frac{P(A \cap B)}{P(A)}$, shows the probability a customer will choose a set of items, given the consumer has already chosen another set of items. It denotes the percentage of transactions containing A which also contain B. It is an estimation of conditioned probability. (Aguinis et al., 2013). Both support and confidence usually appear as percentages, ranging from 0 to 100. "Even if a number of association rules do not notably differ from each other in terms of their support values, they are likely to differ in terms of their confidence values. Thus, compared to support, confidence is capable of more clearly detecting differences in the strengths of association rules” (Aguinis et al., 2013).

An association rule could appear (X→Y) with the X set of items as the antecedent and Y set of items as the consequent. Customers who buy X are likely will buy Y with probability % c (the confidence). The rule may lead to: “Eighty percent of people who buy cigarettes also buy matches” (Ulas, 2001). Briefly, support shows “How often do these items occur together in the data?” and confidence, “How likely are these items to occur together in the data?” (http://docs.oracle.com/cd/E18283_01/datamine.112/e16808/market_basket.htm)

Another aspect is the determining the association rules’ levels where they are actually significant (note, this is not significance in the statistics sense). When we look at the literature, there are different minimum cut off values for confidence level or support level. For example, Goh and Ang (2007) designated 1% as the minimum support level and 40%, 50%, and 60% as three threshold levels for confidence values. Yang et al., (2007) used minimum cut off values of 1.3% for support and 47.6% for confidence. This support value may seem too low; as Cohen et al. (2001) states in their paper , however, support value’s usefulness decreases with very large (e.g., containing millions of transactions) and rich (e.g., containing thousands of items) data sets. In these situations, on average, support values will seem quite low because the presence of other transactions (involving other items) serves as noise in the data set.

A retailer can use this information to inform the following: (http://snowplowanalytics.com/analytics/.html)

- Store layout (put products that co-purchased together close to one another, to improve the customer shopping experience)
- Marketing (e.g. target customers who buy flour with offers on eggs, to encourage them to spend more on their shopping basket).

We will consider the former in our work in this chapter.

5.3 Data Set and Statistical Analysis

The following market basket data comes from the Capitol Migros store in Istanbul. Their Marketing Department provided this data for 10,000 customers and 31,531 items purchased. This is a randomly selected one month sample. These are the transactions that are stored in the SAP system of the company, include the electronic bills or invoices, and contain the items purchased by different customers. The illustration of the transactions data appears in table below.

Cust. no	Category
1	Bakery
1	Cheese
1	Chocolate
1	Cleaning products
1	Coffee/tea
1	Dairy
1	Detergent
1	Meat
1	Oil/ spices
1	Soft drinks
2	Cheese
2	Chocolate
2	Coffee/tea
2	Cosmetics
2	Dairy
2	Detergent
2	Paper products
2	Softdrinks
……………	……………….
……………	……………….
9994	Fruit/veg
9994	Poultry
9995	Alcoholic drinks
9995	Soft drinks
9996	Chocolate
9996	Soft drinks
9997	Alcoholic drinks
9997	Bakery
9997	Soft drinks
9998	Alcoholic drinks
9999	Bakery
10000	Chocolate

Table 5.1 Illustration of 10,000 transactions data taken from Migros.

PRODUCT CATEGORY	NUMBER OF ITEMS PURCHASED	PERCENTAGE
ALCOHOLIC DRINKS	1706	5.41%
BAKERY	1980	6.28%
BOOKSMAGAZINES	1443	4.58%
CHEESE	1327	4.21%
CHOCOLATE	3885	12.32%
CLEANINGPRODUCTS	543	1.72%
COFFEETEA	1711	5.43%
COSMETICS	1164	3.69%
DAIRY	2198	6.97%
DELI	369	1.17%
DETERGENT	897	2.84%
ELECTRONICS	180	0.57%
FISH	180	0.57%
FROZENFOOD	1043	3.31%
FRUITVEGITABLES	2685	8.52%
HOUSEHOLD	919	2.91%
MEAT	1238	3.93%
OILSPICES	1043	3.31%
ORGANICFRUITS	637	2.02%
PAPERPRODUCTS	1103	3.50%
POULTRY	478	1.52%
SNACKSNUTS	347	1.10%
SOFTDRINKS	4060	12.88%
TEXTILE	188	0.60%
TOYSPET	207	0.66%
	31531	**100.00%**

Table 5.2 Number of items purchased per each category and their percentage

Table 5.2 shows the number of items purchased from each product category with the percentage in total transactions; this information is not suffice, however, if we want to figure out the interrelationships between product categories. So, we loaded an Excel table to Matlab and wrote a simple code to see the co-occurrences of product pairs. For instance, the customers who purchased soft drinks and coffee /tea appear in the Matlab code as follows:

```
clear all;clc;clf;close all;
% [n,t]=xlsread('migrosdata.xlsx');
% c = t(2:end,2); clear t;
% m = 10000; % Total number of Customers
% n ---> custno
% c ---> category
load mix.mat
s1 = n(strcmpi(c(:,1),'softdrinks'));
s1(diff(s1)==0) = [];
s2 = n(strcmpi(c(:,1),'coffeetea'));
s2(diff(s2)==0) = [];
s3 = zeros(m,1);
s3(s1) = s3(s1)+1;
s3(s2) = s3(s2)+1;
ss = find(s3==2); % Customers buying s1 and s2
ns = length(ss)  % Number of Customers buying s1 and s2
```

This calculation, done for each of the 25 departments and it is shown in Table 5.3 below. Then, we calculated support, confidence and lift for this data set. From the same example, the lift association rule between coffee/ tea and soft drinks is calculated as follows: (711/10,000)/((1711/10,000)*(4060/10,000)= 1.024.

With lift slightly greater then 1, we also check the support value and the confidence value. Support is 711/10,000=7.11%. Confidence is (711/10,000)/(1711/10,000)=42 %. The probability of purchasing coffee /tea, given also purchasing soft drinks, totals 42%.

	with softdrinks	total item purchased	support	confidence	lift
alcoholic drinks	486	1706	4.86%	28.49%	**0.702**
bakery	833	1980	8.33%	42.07%	**1.036**
booksmagazines	551	1443	5.51%	38.18%	**0.941**
cheese	554	1327	5.54%	41.75%	**1.028**
chocolate	1777	3885	17.77%	45.74%	**1.127**
cleaning products	239	543	2.39%	44.01%	**1.084**
coffeetea	711	1711	7.11%	41.55%	**1.024**
cosmetics	476	1164	4.76%	40.89%	**1.007**
dairy	909	2198	9.09%	41.36%	**1.019**
deli	175	369	1.75%	47.43%	**1.168**
detergent	381	897	3.81%	42.47%	**1.046**
electronics	59	180	0.59%	32.78%	**0.807**
fish	70	180	0.70%	38.89%	**0.958**
fruitveg	765	2685	7.65%	28.49%	**0.702**
household	383	919	3.83%	41.68%	**1.026**
meat	500	1238	5.00%	40.39%	**0.995**
oilspices	455	1043	4.55%	43.62%	**1.074**
organic fruits	271	637	2.71%	42.54%	**1.048**
paper products	460	1103	4.60%	41.70%	**1.027**
poultry	209	478	2.09%	43.72%	**1.077**
snacksnuts	155	347	1.55%	44.67%	**1.100**
textile	59	188	0.59%	31.38%	**0.773**
toyspet	69	207	0.69%	33.33%	**0.821**

Table 5.3 Each department's purchase quantity with the soft drinks department and the associated support, confidence, and lift values.

According to the analysis shown in the table above, 47% of people who buy deli also buy soft drinks. A stronger relationship exists between product categories and chocolate; 57% of people who buy poultry also buy chocolate. The paper products category and dairy category also have strong relation with the chocolate department. The strongest relationship found in this analysis is between fish and fruit; 63 % of customers who buy fish also buy fruit and 62 percent of customers who buy organic fruits also buy fruits and vegetables. The support value is not high for fish and fruit although the confidence and the lift seem high; this means the frequency of buying fish and fruit /vegetables equals 1.14%. As mentioned earlier, the meaning of the support value decreases in the presence of large data sets. (We have 10,000 transactions) Furthermore, Aguinis et al. (2013) states "even if a number of association rules do not notably differ from each other in terms of their support values, they are likely to differ in terms of their confidence values.

Thus, compared to support, confidence is capable of more clearly detecting differences in the strengths of association rules". For determining a layout, generally both lift and confidence values are taken into account.

When we search the marketing literature, authors choose the minimum values of association rules by considering the market conditions. The minimum support and minimum confidence parameters are a user choice. So, we considered the previous research for supermarket data. Choosing a minimum confidence level 40% together with a minimum lift value of 1.1, a positive association rule between departments appears in Table 5.5.

Related Categories	Support	Confidence	Lift
Oilspices-Coffeetea	5.02%	48%	2.81
Poultry-Coffeetea	2.25%	47%	2.75
Cheese-Coffeetea	5.83%	44%	2.57
Cheese- Bakery	6.53%	49%	2.48
Detergent-Coffeetea	3.80%	42%	2.48
Cleaningproducts-Coffeetea	2.30%	42%	2.48
Fish-Fruitsvegetables	1.14%	63%	2.36
Meat-Coffeetea	4.93%	40%	2.33
Organicfruits-Fruitsvegetables	3.96%	62%	2.31
Poultry-Fruitsvegetables	2.62%	55%	2.04
Meat-Bakery	5.00%	40%	2.04
Meat-Fruitsvegetables	5.48%	44%	1.65
Oilspices-Fruitsvegetables	4.60%	44%	1.64
Poultry-Chocolate	2.71%	57%	1.50
Coffeetea-Chocolate	9.55%	56%	1.43
Detergent-Chocolate	4.90%	55%	1.41
Cheese-Chocolate	7.11%	54%	1.38
Paper-Chocolate	5.76%	52%	1.34
Dairy-Chocolate	11.40%	52%	1.31
Cosmetics-Chocolate	5.95%	51%	1.31
Deli-Softdrinks	1.75%	47%	1.17
Chocolate-Softdrinks	17.70%	45%	1.13
Snacksnuts-Softdrinks	1.55%	45%	1.10

Table 5.4 Market Basket Data Mining Results

At the end of calculations (also checking the reverse pairs), the highest lift value belongs to oil/spices and coffee/ tea - 2.81, the second highest to poultry and coffee /tea and the third highest to-cheese-bakery. The highest support value, between chocolate and soft drinks, totals 17.7%. Lift and support values are symmetric. This means that the support value between soft drinks and chocolate is also 17.7%. In a similar way, the lift values are same for all reverse pairs.

Between coffee/ tea and oil spices it is 2.81. However, the confidence level between oil spices and coffee/ tea is 29.3%. People buying oil spices who also buy coffee tea is not the same as people buying coffee/tea who also buy oil spices. As we mentioned earlier, the reverse pairs of departments are also checked and since some of the departments' reverse pairs' confidence levels are below the cutoff point, they are not listed in the table. These results were presented to the CRM department and they stated that Migros works with a consulting company for analyzing their market basket data and our results were consistent with their analysis. This table was also validated by the Migros Planning Department. The planning department engineers found the results logical and reasonable according to their previous experience.

5.4. Adjacency matrix

"Gaining insight on product interdependencies can help retailers optimize store layout. It is an important aspect of retailing business because in-store settings may help increase sales if done right." (Cil, 2012). Retailers must put items that are purchased together close to each other not only to increase sales but also to improve customers' shopping experiences.

In classical facility layout problems, adjacency matrix is used especially to reduce the material handling costs and group functional areas; one widely used approach involves the use of the REL chart. "An REL chart, defined by Muther (1973), is a table that summarizes estimates of the desirability of locating facilities next to each other" (Yapicioglu, 2008). We will use the REL scores that are provided in Table 5.6. In measuring the layout efficiency, the well-known closeness ratings concept from the manufacturing facilities layout literature is used (see, for example, Heragu 1997, Tompkins et al., 2003 or Yapicioglu, 2008).The layout efficiency is denoted by ε and calculated by the formula given below:

$$\varepsilon = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(c_{ij}^{+}x_{ij}\right)-\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(c_{ij}^{-}\left(1-x_{ij}\right)\right)}{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}c_{ij}^{+}-\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}c_{ij}^{-}} \quad \text{where} \qquad (5.1)$$

$$x_{ij} = \begin{cases} 1, & \textit{department i is adjacent to department j} \\ 0, & \textit{otherwise} \end{cases}$$

Rating	Definition	c_{ij}
A	Absolutely Necessary	125
E	Especially Important	25
I	Important	5
O,U	Ordinary Closeness	0
X	Undesirable	-25
XX	Prohibited	-125

Table 5.5 Adjacency Ratings used.

Corresponding closeness ratings, denoted by c_{ij} in Table 5.5, are determined using an exponential scale, as suggested by Askin and Standridge (1993). We considered departments adjacent, if they share a common edge, if they are face to face each other or they are separated only by an aisle. For better understanding, layout of the store is given in Figure below. Departments A and B, B and C, E and D, F and E, F and D are adjacent. When the racetrack aisle separates departments, they are not considered adjacent due the lack of strong interaction. For instance, department C and D are not included as adjacency calculations. A customer at department C would only see the end cap of department D. Department D is adjacent only to department E and F in our model.

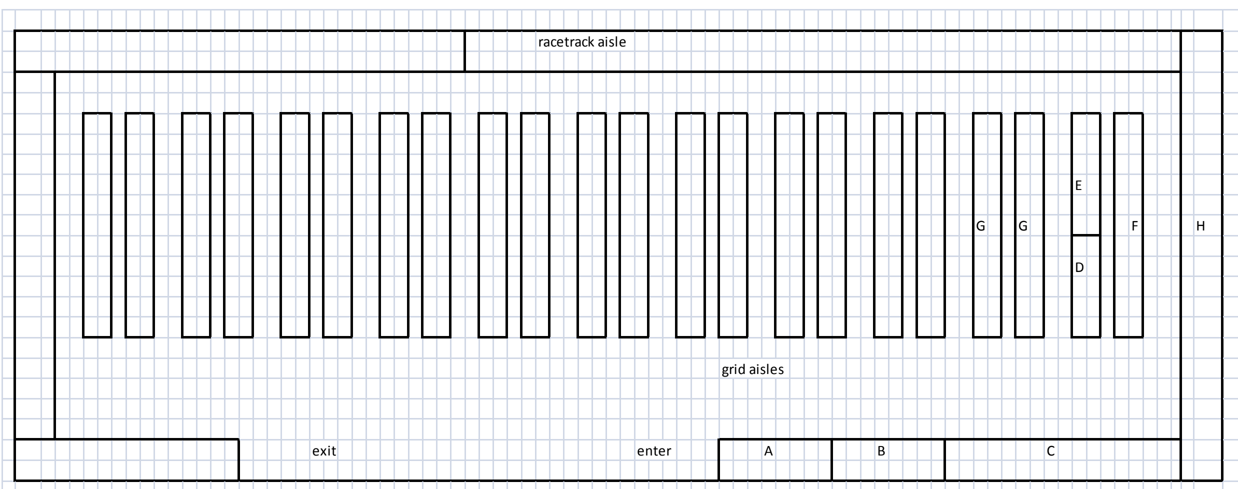

Figure 5.1 Simple Layout Representation of the store

Departments having a REL score of -25 cannot be placed next to each other. Even if they are not in the same grid aisle, they cannot be located on adjacent grid aisle. For example, if G and E have a -25 adjacency score, the algorithm will not let them to be located as shown in Figure 5.1.

In a same way, E, D and F cannot have a negative score since they are located in the same grid aisle. In grocery stores, product categories are basically divided into two major parts, food products and non-food products. For instance deli department is an example for food department and cleaning products department is an example of non-food department. Store managers generally avoid placing food departments next to non-food departments in practice. Even they are in separate grid aisles, they prefer to cluster food products in one part of the store and non-food products in the other side of store. This constraint is added because of this reason.

The main point involves translating the association rule numbers to REL chart. A simple algorithm is used in this step. Basically, the highest support, lift and confidence valued department pairs are considered as “Absolutely necessary” in closeness rate. According to Table 5.5, the department pairs which have confidence level over 60 % are also rated as “Absolutely necessary”. The department pairs that have confidence level between 60% and 55% are rated as “Especially imported”. The department pairs that has confidence level between 55% and 40% and also satisfies the minimum lift and support value are rated as “Important”. Furthermore, from the interview with the Capitol Migros store manager, the departments which he strongly believes are related with each other are also included in the REL chart. He believes that locating the fish department close to the fruit and vegetables department will make customers spend time in the fruits department while waiting for the preparation of their fish orders. He strongly recommends that the textile department and the cosmetics department be close, as especially enticing to women customers. He also added that the tea / canned food / sugar department and oil and spices departments should be close to each other as they are complementary. He also mentioned that food products cannot be located next to cleaning products or detergent. These kinds of prohibitive relationships are added to the chart with negative values.

This output of market basket analysis are presented in Head Office of Migros, Istanbul and approved before inserted to the optimization part. The REL chart prepared for Migros Capitol store is given below.

NO	DEPARTMENT	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	**ALCOHOLIC DRINKS and TOBACCO**		0	0	5	25	-25	0	0	25	-25	-25	5	0	0	0	5	0	0	0	5	25	5	0	0	-25
2	**BAKERY**			0	25	0	-25	0	0	0	-25	-25	0	0	0	0	0	0	0	-25	-25	0	0	0	-25	-25
3	**BOOKS and MAGAZINES**				0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	**CHEESE OLIVES**					25	-25	0	0	0	-25	-25	0	0	0	0	0	0	0	-25	0	0	0	25	0	-25
5	**CHOCOLATE and COOKIES**						-25	0	0	0	-25	0	0	0	0	0	0	0	0	0	25	0	25	25	0	0
6	**CLEANING PRODUCTS**							0	-25	-25	25	-25	-25	-25	-25	0	-25	0	-25	0	-25	-25	-25	-25	0	25
7	**COSMETICS**								0	0	0	0	-25	25	-25	0	-25	0	0	0	-25	0	0	0	25	0
8	**DAIRY MILK YOGURT**									0	-25	-25	0	0	0	0	0	0	0	-25	0	0	0	0	0	-25
9	**DELI/SIDE DISH**										-25	0	0	0	0	0	5	0	0	-25	25	0	0	0	-25	-25
10	**DETERGENT**											0	-25	-25	-25	0	-25	0	-25	25	-25	-25	-25	0	0	0
11	**ELECTRONICS**												-25	0	0	0	0	0	-25	0	0	0	0	0	0	0
12	**FISH**													0	125	0	0	0	0	0	0	0	0	0	-25	-25
13	**FROZEN FOOD and EGG**														0	0	0	0	0	0	0	0	0	0	0	-25
14	**FRUIT and VEGETABLES**															0	0	5	125	0	25	0	0	0	0	-25
15	**HOUSEHOLD (season nonfood)**																0	0	0	0	0	0	0	0	0	0
16	**MEAT SECTION**																	5	0	-25	25	0	0	5	0	-25
17	**OIL and SPICES (beans and lentils)**																		0	0	5	0	0	125	0	0
18	**ORGANIC FRUIT and VEGETABLES**																			0	0	0	0	0	0	0
19	**PAPER PRODUCTS**																				0	0	0	0	0	0
20	**POULTRY**																					0	0	0	0	-25
21	**SNACKSNUTS**																						5	0	0	0
22	**SOFT DRINKS (juices)**																							5	-25	0
23	**TEA CANNED FOOD SUGAR BREAKFAST**																								0	0
24	**TEXTILE and SHOES**																									0
25	**TOYS and PET**																									

Table 5.6. REL Chart of Migros Store.

We used the data mining information in this dissertation in the optimization part. The layout efficiency ε will be calculated as an objective function together with total revenue. The store layout that has maximum efficiency score will be compared with the layout that has maximum revenue. Another approach is multi-objective optimization. This makes more sense since the algorithm optimizes both scores at the same time.

Chapter 6

Heuristic Procedures for the Grocery Store Layout Problem

This chapter presents heuristic methods for the grocery store layout problem (GSLP). As mentioned in Chapter 3, the mathematical model describing the problem consists of too many constraints and decision variables for commonly computing power, especially when including 10 or more departments in the layout. Heuristic methods may work to solve the problem, however, irrespective of these limitations.

To solve the GSLP, we present two constructive heuristics in this chapter followed by tabu search (TS). We initially developed TS for single-objective of maximizing total revenue; then, to find a more effective layout and to present decision-makers more options, we moved to a bi-objective approach to maximize not only total average revenue but also the adjacency score. We describe below each of these methods step-by-step and then apply them to the Migros Capitol Store. Using the proposed layouts, each simulation model is run to compare the total revenue and adjacency scores of the resultant layout. Finally, we discuss the performance of the constructive heuristics and TS algorithms.

6.1. Constructive Heuristic without constraint for GSLP

The inputs of this heuristic are REL scores, unit revenue per day per meter, and current lengths of each department. By considering the limited area of the store, and with the guidance of the store managers, we calculated the minimum length requirement by reducing twenty percent of the current length and, likewise, we calculated the maximum length by incrementing twenty percent of current length. We initially assumed revenue to behave linearly, but as described further in Section 6.7, by considering the space elasticities of product categories, we calculated diminishing returns in revenue with respect to length. The current layout of the store appears in Figure 6.2. The steps of the heuristic include the following:

Step 1: Sort departments from longest minimum length to shortest minimum length, and check for departments having minimum length greater than the grid bay length. Assign departments having a minimum length greater than the grid bay to the racetrack aisle with their minimum length. Calculate the remaining length of the racetrack aisle after assignment.

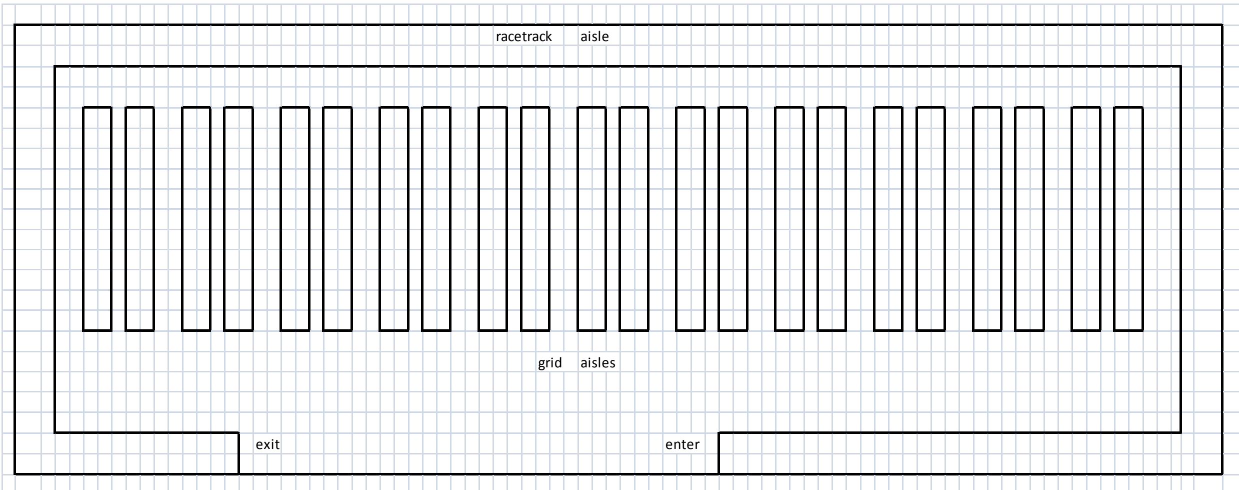

Figure 6.1 Definitions of aisles for the constructive heuristic.

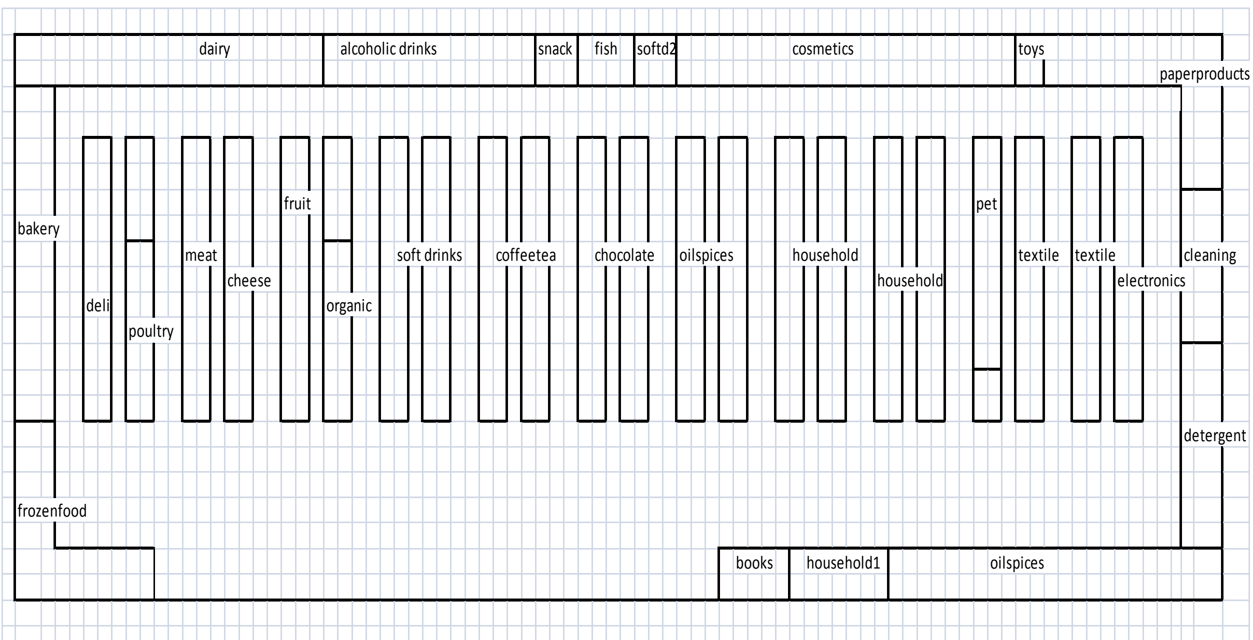

Figure 6.2 Current Layout of the Store

As seen in Figure 6.2 (the current layout), some departments appear in both grid and racetrack aisles because of the large area requirement -for instance, household department. This may cause an uncomfortable shopping experience, so in this dissertation; we assign each department to only one location and do not allow for separation of the departments. Using the total revenue of the current layout as 121,972TL and the total shelf length as 369m, we calculated the adjacency score as 0.44 with Equation 5.1.

Step 2: Check the adjacency scores of the assigned departments from the adjacency matrix given in Chapter 5. Place the department pair with the highest adjacency score next to each other on the racetrack bay with their minimum length; if two or more adjacency scores are equal, the department pair with the highest revenue is placed first. Calculate the remaining length of the racetrack bay. Subsequent pairs are placed from highest to lowest adjacency score, calculating the remaining racetrack bay length after each department pair is added.

Step 3: Start filling grid aisles by first sorting the unassigned departments from longest minimum length to shortest minimum length. If two or more departments have the same minimum length, they are ranked (from highest to lowest revenue). Select the highest unit revenue department among longest minimum lengths and assign this department to the first grid aisle. Check if the bay can be filled with this department. (Check the maximum length of the assigned department. If it is equal or greater than the grid bay length, the length of department is equal to grid bay length. The grid bay length is 19 meters for our store) Go to the next grid aisle and check the adjacent department of the department on the first grid aisle. Place the department with the highest adjacency score on the second grid aisle with their minimum length; if two or more adjacency scores are equal, the department with the highest revenue is placed first. The remaining length of the grid aisle is calculated. List the departments whose minimum and maximum length range is between the remaining lengths of the grid aisle. If there is more than one department, choose the one that has highest unit revenue and assign this department to the second grid bay. Adjust the lengths by keeping total bay length fixed. (Compare the revenues of assigned departments and increment the one that has higher unit revenue until the total reaches the grid aisle length.) Go to next grid aisle and check the adjacent departments of the department on the second grid aisle. Following this decision rule, finalize assignment of departments to all grid aisles.

Step 4: Assign the rest of the unassigned departments to the racetrack aisle with their minimum lengths. Temporarily assign order departments in ascending order of department numbers. Then check the adjacency matrix. Sort all departments in the racetrack aisle according to their revenues. Recalculate the total remaining length. If it is greater than zero, increment the length of the department having the highest revenue from minimum length to maximum length. When ordering the departments, check the adjacency matrix and do not place departments that have negative values in the matrix next to each other. Recalculate the total remaining length and if there is still room in the racetrack aisle, increment the length of second highest unit revenue department until the excess space reaches zero.

NO	DEPARTMENT	revenue(TL)	current(m)	min(m)	max(m)
1	ALCOHOLIC DRINKS and TOBACCO	731.4	18.0	14	22
2	BAKERY	433.0	13.0	10	16
3	BOOKS and MAGAZINES	270.6	8.0	6	10
4	CHEESE OLIVES	1055.6	9.0	7	11
5	CHOCOLATE and COOKIES	469.3	23.0	18	28
6	CLEANING PRODUCTS	123.6	13.0	10	16
7	COSMETICS	333.2	22.0	18	26
8	DAIRY MILK YOGURT	269.3	23.0	18	28
9	DELI/SIDE DISH	345.9	15.0	12	18
10	DETERGENT	242.2	19.0	15	23
11	ELECTRONICS	259.4	8.0	6	10
12	FISH	424.0	5.0	4	6
13	FROZEN FOOD and EGG	345.9	9.0	7	11
14	FRUIT and VEGETABLES	516.8	15.0	12	18
15	HOUSEHOLD (season nonfood)	110.8	31.0	25	37
16	MEAT SECTION	673.4	10.0	8	12
17	OIL and SPICES (beans and lentils)	159.5	27.5	22	33
18	ORGANIC FRUIT and VEGETABLES	362.2	6.0	5	7
19	PAPER PRODUCTS	325.8	18.0	14	22
20	POULTRY	503.6	5.0	4	6
21	SNACKSNUTS	443.5	6.0	5	7
22	SOFT DRINKS (juices)	186.7	22.5	18	27
23	TEA CANNED FOOD SUGAR BREAKFAST	440.1	17.0	14	20
24	TEXTILE and SHOES	35.8	18.0	14	22
25	TOYS and PET	115.4	8.0	6	10
			369.0		

Table 6.1 Unit revenue per department per day and the minimum, maximum and current department lengths for the Migros Store

6.2. Implementation

For better understanding the described heuristic, an example is explained below step by step:

1. Sort departments from largest minimum length to smallest minimum length. (We consider the department numbers according to Table 6.1.)

15,17,5,7,8,22,10,1,23,19,24,14,9,2,6,16,4,13,3,11,25,21,18,20,12.

2. Assign the minimum length of any department that has a minimum length greater than 19 to the racetrack bay. Start with the department that has longest minimum length.

Department 15 with 25m length and department17 with 22m length are assigned to racetrack aisle.

3. Calculate total remaining length of the racetrack bay. (160-25-22=113m)

4. Check the adjacency of the departments that have been assigned to the racetrack bay.

Department 15 has no adjacency scores greater than 0. Department 17, however, has the maximum adjacency score of 125 with Department 23. Therefore, Department 23 is assigned next to Department 17.

5. Recalculate the remaining length in the racetrack aisle. (113-14=99m)

6. Go to the grid layout. Each grid aisle length is fixed and is 19m. Take the department with the longest minimum length. If there is more than one department with the same length, choose the one that has highest unit revenue.

Department 5 has a minimum length of 18 and among the other departments with same minimum length has the highest unit revenue.

Department 5 is assigned to 1st grid bay. Total remaining length is 19-18=1. Can I fill the aisle with department 5? (Checks the maximum length of department and it is 28m) So, department 5 is assigned as 19m.

7. Check the adjacent departments of department 5.

1, 20, 22 and 23 each has a 25 adjacency score. We will choose the one that has highest unit revenue. Department 1 is assigned to 2nd grid bay. Department 1 has minimum length of 14. Can I fill the aisle with department 1? (Check the maximum length of department 1 and it is 22m.) So, department 1 is assigned as 19m.

8. Check the adjacent departments of department 1.

9 and 21 each has a 25 adjacency score. We will choose the one that has highest unit revenue so department 21 is assigned to 3rd grid aisle. Department 21 has 5 minimum length and 7 maximum length. So we assign it as 5m and the remaining length is 19-5=14m.

9. Check departments that have length min<=14<=max.

These departments are 2,6,9,14,19,23,24. First, we check the adjacency matrix if any of these departments should be adjacent to department 21. There is no department that can be placed next to department 21. Department 6 cannot be next to department 21. Then we look for the department with the highest unit revenue. Department 14 has the highest unit revenue so we place department 14 next to department 21 with minimum length. The minimum length of department 21 is 5m. The total length of the aisle is 5+12=17. This is less than the length of grid aisle. There should be no room in the aisle. To decide to increment which department, we compare the unit revenues. When we compare the revenues of department 21 and department 14, department 14 has higher unit revenue so we increment the length of department 14 to 14m. The remaining length is 0.

10. Go to the next grid aisle. Check the adjacent departments of department14.

Department 14 has a 125 adjacency score with department 12 and department 18. We choose the one with higher unit revenue. Department 12 has the higher unit revenue. Department 12 is assigned its minimum length of 4. The remaining length is 14. Department 18 has 5m minimum length so it is placed next. The remaining length is =15-5=10m.

11. Check departments that have length min<=10<=max.

These are 2,3,4,6,11,13,16,25. We check the adjacency matrix if any of these departments are adjacent to department 18. There is no adjacent department but department 6 and department 11 cannot be located next to department 18. Then we check the unit revenues. Department 4 has the highest unit revenue. So we assign department 4 with minimum length to this aisle. The total length of aisle is 4+5+7=16m. The aisle is not filled yet. So, we compare the revenues of assigned departments in this aisle to choose the department we will increment the length. Department 4 has highest unit revenue and we increment it from 7 to 10. We arrange the lengths in the bay as department 12 4m, department 18 5m and department 4 as 10m.

12. Go to next grid aisle. Check the adjacent departments of department 4. There is no adjacent department. So we take the department with highest minimum length and highest unit revenue of those minimum lengths. Department 7 is assigned to 5^{th} grid aisle.

13. In this way we fill the grid aisles and then assign the rest of the unassigned departments to the racetrack aisle. So departments to be placed in the racetrack aisle are 15,17,23,8,10,11,13,25.

14. Sort these departments from highest unit revenue to lowest unit revenue and assign the maximum length to the one that has highest unit revenue. Repeat and recalculate the remaining length of racetrack aisle until it reaches 0. So the departments' lengths are as follows:

Department 23:20, department13:11, department 8:28, department 11:10, department 10:23, department 17:32, department 25:10, department 15:26.

15. Check the adjacency scores of these departments and order them. The sequence before the order was 15,17,23,8,10,11,13,25. We started from the longest minimum length, then the other department that exceeds the length of grid aisle. The adjacent department to 17 was 23. And the rest of unassigned departments (that couldn't be assigned to grid aisles) are temporarily assigned according to department number in ascending order. To sort the departments in the racetrack aisle, we start to check the adjacency matrix. The first department that will be checked is department 8. Can I assign department 8 next to department 23? There is no negative value in the matrix so department 8 stays next to department 23. Then, can I assign department 10 next to department 8? No. The value in adjacency matrix is -25. So, I moved department 10 to the starting point, in front of department 15.I check the adjacency of department 15 and 10. There is

no negative value. Then, I go back next to department 8. Can I assign department 11 next to department 8? No. So, department 11 goes in front of department 10. I check the adjacency matrix. There is no problem for department 10 and department 11 to be next to each other. In a same way, I ask if I can assign department 13 next to department 8. There is no problem. So department 13 keeps its place next to department 8. Then, can I assign department 25 next to department 13? No. Department 25 goes in front of department 11. We check the adjacency matrix. There is no problem. The final sequence of racetrack aisle is 25,11,10,15,17,23,8,13.

The total remaining length of racetrack aisle is 160-113=47. According to the highest unit revenue, we assign the length of department from minimum to maximum length. So, department 23 has highest unit revenue, we increase length from 14 to20. The total left length=46-6=40.The second highest is department 13. Then we increase length from 7 to 11. The total left length=40-4=36.This keeps going until the remaining length reaches 0.

The constructive heuristic is applied to the Migros Capitol store and the resultant layout is given in Figure 6.3. The total revenue of the store increases and the new adjacency score of the proposed layout exceeds the current layout.

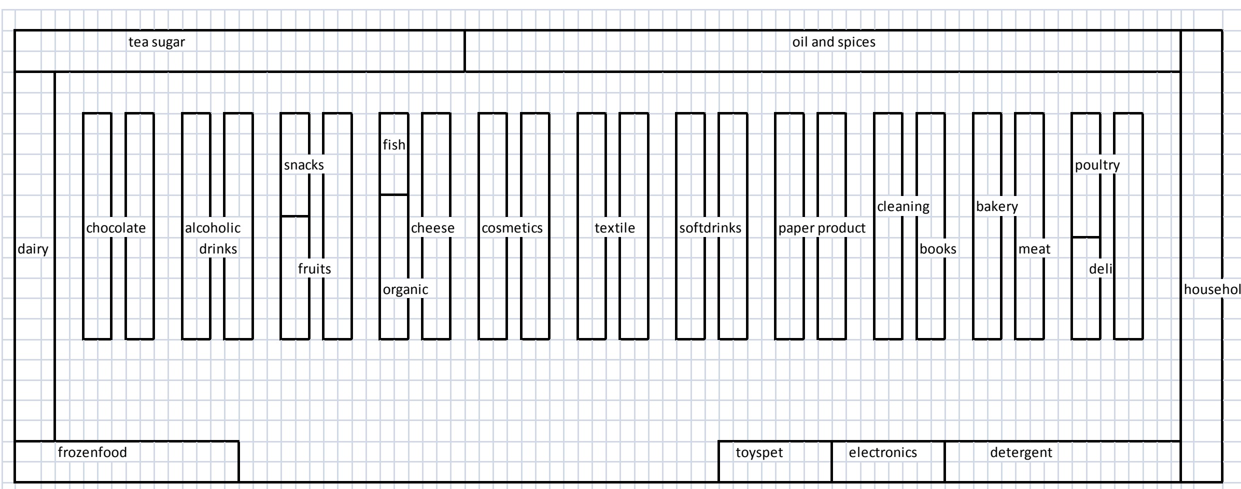

Figure 6.3 Resultant Layout of Constructive Heuristic

Total Revenue= 122,108TL/day

Adjacency=0.55

6.3. Constructive Heuristic with constraint

When analyzing the outputs of the constructive heuristic, we note departments, such as bakery, fish and snack/nuts, appear in grid aisles. In practice, however, grocery stores place these departments in the racetrack aisle due to the need for extra space associated with tools necessary for these departments - for example, a bakery can only be located near ovens. So, we added a constraint to the heuristic, placing the bakery, fish and snack/nuts departments in the racetrack. Additionally, the managers prefer to place the fruits and vegetables department together with fish department and organic fruits department in the racetrack aisle based on the habits of Turkish customers. We accomplished these constraints by adding an initial step "assigning departments 2, 12, 14 and 21 and their adjacent departments to the racetrack aisle". The order of departments in the racetrack is determined according to the adjacency scores. Starting from department 2, we check the adjacent departments of 12, 14, and 21. Then sort them from highest score to lowest. Department 12 and 14 has 125 score, department 18 has 125 score with department 14. Department 4 has 25 score with department 2 and department 21 has 25 score with department 1. It is not important from which one we start. So, department 12, 14 and 18 placed next to each other. Department 2 and department 12 has 5 score so we assign 2 to the other side of 12. Department 21 has 0 adjacency score with 18 or 2 so we made a choice and put department 21 next to 18. Finally, department 1 is assigned next to 21 since they have 25 adjacency score. We assign all of the departments in the racetrack aisle their minimum lengths. Then, calculate the remaining length on the racetrack aisle. We start to fill the grid aisles with the longest minimum length department. If there is more than one, we choose the one that has highest unit revenue. The rest is the same as in the constructive heuristic of the last section.

The resultant layout appears in Figure 6.4.

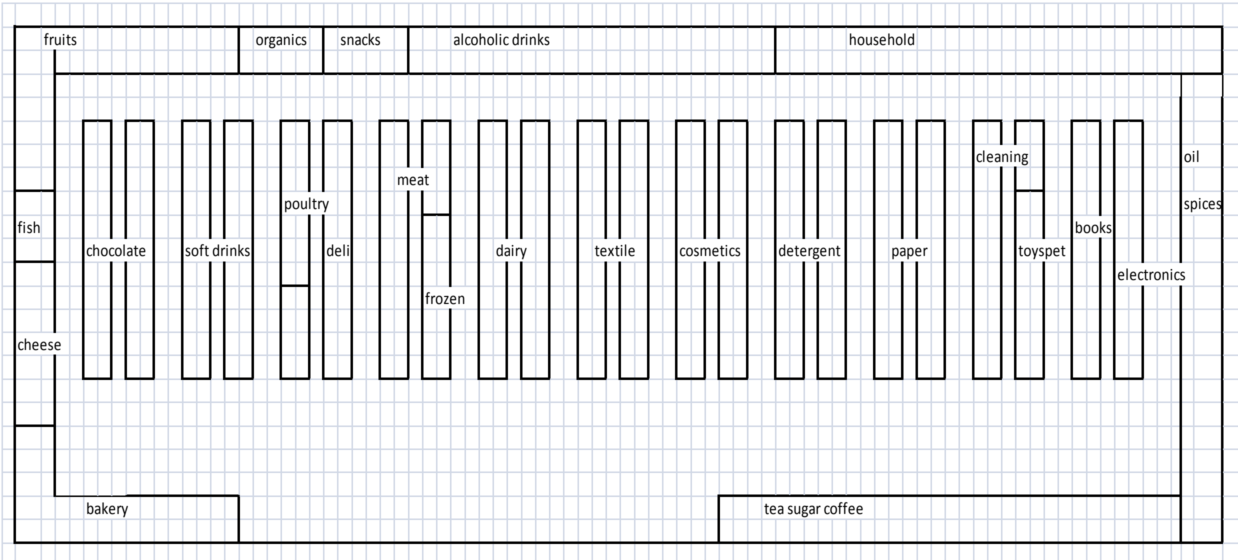

Figure 6.4 Resultant Layout of Constructive Heuristic with constraint

The new layout has better total revenue and adjacency score when compared with the constructive heuristic without constraint (total revenue =128,947TL/day and adjacency score=0.63).

6.4. Performance Assessment of the Constructive Heuristics

In this section, we evaluate the results of the two constructive heuristic are evaluated based on adjacency and total revenue/day, calculating the adjacency score by using the formula in Chapter 5. We assume as adjacent those departments sharing an edge or departments having a common aisle or grid bays next to each other. For departments separated by an aisle, two departments are adjacent if they lie across from each other. The denominator calculates the maximum possible REL score -an ideal layout from the adjacency point of view (Yapicioglu, 2008); the numerator calculates the REL score for resultant layout; and the fraction gives the adjacency efficiency of the layout.

According to the results given above, the best adjacency rate occurred with the constructive heuristic with constraints. It is unusual to add a constraint and obtain a better solution . Given the current layout having an adjacency 0.44 and both heuristics improved the adjacency efficiency. Adding a constraint to constructive heuristic 1 increased the adjacency rate to 0.63, however, total revenue improved to 129,000TL- around 122000TL in the current layout. The constraints impacted the total revenue because the departments constrained to the racetrack aisle are the ones with high unit revenue; since the racetrack aisle has more length, the algorithm increased the length of these high unit revenue departments to the maximum level so more revenue was obtained.

6.5. TS for GSLP

In addition to constructive heuristics, as another optimization tool, we used a TS algorithm is used in this project. TS, a powerful algorithmic approach, has seen success in handling the complicated constraints of real life problems (Gendreau and Potvin, 2010) such as in quadratic assignment problems (Taillard 1991), unequal area facility layout (Kulturel-Konak et al., 2004), vehicle routing (Taillard et al., 1997), redundancy allocation (Kulturel-Konak et al., 2003) and job shop scheduling (Barnes and Chambers, 1995). The details of proposed TS algorithm are as follows:

1. Solution Representation: A 3*25 matrix represents the layout. (25 departments) The first row indicates the bay number assigned to department, the second row shows the ordering of the departments starting from next to the exit and continuing counterclockwise around the racetrack aisle (Bay 12 is the racetrack aisle) and for the grid aisles the ordering starts from top to bottom. The third row states the length of department in the bay. The proposed layout of constructive heuristic 1 with constraint illustrated in Figure 6.3 can be represented as Table 6.3.

						bay																		
						Dep.																		
						length																		

Table 6.2 Matrix representation of layout

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	4	5	6	7	8	9	10	10	11	11
2	4	12	14	18	21	1	15	17	23	5	22	20	9	16	13	8	24	7	10	19	6	25	3	11
16	11	6	18	7	7	22	24	29	20	19	19	6	13	12	7	19	19	19	19	19	13	6	10	9

Table 6.3 Matrix representation of the proposed layout of the constructive heuristic with constraint

The inputs to the algorithm include the bay lengths, (racetrack bay with 160m length and 11 grid bays with 19m length each), the minimum and maximum lengths of the departments, the unit revenues per length of these departments and the adjacency matrix. The algorithm operates on a layout represented as a matrix as shown in Table 6.2. A feasible initial solution is identified randomly according to following constraints:

- Length constraint: Departments must fit in the range of minimum and maximum length – the racetrack bay length must equal 160m, and 11 grid bays must equal 19m each; and
- Adjacency Constraint: Departments having REL score of -25 cannot be placed next to each other. For instance, we cannot locate the dairy department next to the pet and toys department in the same grid. Furthermore, even they are not in the same grid, they cannot be located on adjacent grid aisle.

2. Move operator: We use a swap operator to exchange places of two departments located in the same bay or in the i^{th} and j^{th} bays. The number of solutions reachable using the swap operator equals $n*(n-1)/2$ =25*24/2=300.

As mentioned before, our problem has two important constraints: length (minimum and maximum lengths) and adjacency (departments preferably next to each other or departments preferably not next to each other). These two constraints complicate the swap operation, no problem arises for departments having almost equal length but for departments having totally different lengths, we need a repair function. Even when repaired; no feasible solution may arise- for instance, consider the initial solution given below:

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	4	5	6	7	8	9	10	10	11	11
2	4	12	14	18	21	1	15	17	23	5	22	20	9	16	13	8	24	7	10	19	6	25	3	11
16	11	6	18	7	7	22	24	29	20	19	19	6	13	12	7	19	19	19	19	19	13	6	10	9

Table 6.4 An example of an initial layout

If we swap department 4 in the 12^{th} bay with department 5 in the 1^{st} bay, a problem occurs since the minimum length of department 4 equals 7 and the maximum length of department 4 equals 11. To keep the total length of 1^{st} bay 19, assign another department to fill the room. Which department will fill the room? Start searching from department 2 to department 11. We cannot assign departments 2, 12 or 14 to grid bays. We can swap department 18 but it is 7+11=18<19 makes it infeasible. Department 21 should stay in the racetrack bay. Department 1 has a minimum length of 14, and 14+7=21>19 makes it infeasible. Department 15 has a minimum length of 24 -infeasible. Department 17 has a minimum length of 22 -also infeasible. After checking all of the departments, swapping department 5 and department generates an infeasible layout. Even if it is feasible, we need an extra department to fill the room, the bay structure of the department will change and this means a drastically new layout. We must derive a new method.

In the new method, repair is unnecessary. First, take as an input a randomly-generated department sequence string (second row). Then, for that department string, generate all possible bay strings (first row). The constraint is that total minimum lengths of departments in the bay<= bay length<=total maximum lengths of departments in the bay. The algorithm searches until no feasible bay strings and unassigned departments exist.

In the second step, generate the length string (third row). From all possible bay strings and the given department string, assign the lengths of departments by considering the minimum and maximum length constraints and calculate the total revenue each time. Choose the layout giving the maximum total revenue. Then in TS, swap departments, transfer the new department string to the algorithm and proceed as above. This method only moves the department sequences and finds the bay breaks and lengths to be the best possible for a given sequence.

3. Tabu List Entries: Store the most recently swapped department pairs in the tabu list. This prohibits the pair from being swapped again during its duration on the tabu list. Using a uniform distribution with a lower- and upper- bound dynamically changes the size of the tabu list.

4. Neighborhood Definition: The generation of the neighborhood occurs by swapping department *i* and *j*.

5. Objective Function: A single objective function of the problem involves maximizing total revenue (TR).

6. Aspiration Criteria: If a solution within the neighborhood has a better objective function value than the best solution found so far, allow a move to that solution even if tabu.

7. Candidate List Strategy: n*(n-1)/2 solutions can occur by swapping the departments. Check all possible bay structures of the department sequences and choose the best bay structure for a given department sequence.

8. Termination Criteria: First, choose a certain number of iterations (e.g., 500 iterations) as a termination criterion. Then, as a second strategy, if the best solution has not improved for a certain number of consecutive moves (e.g., 50), the search terminates.

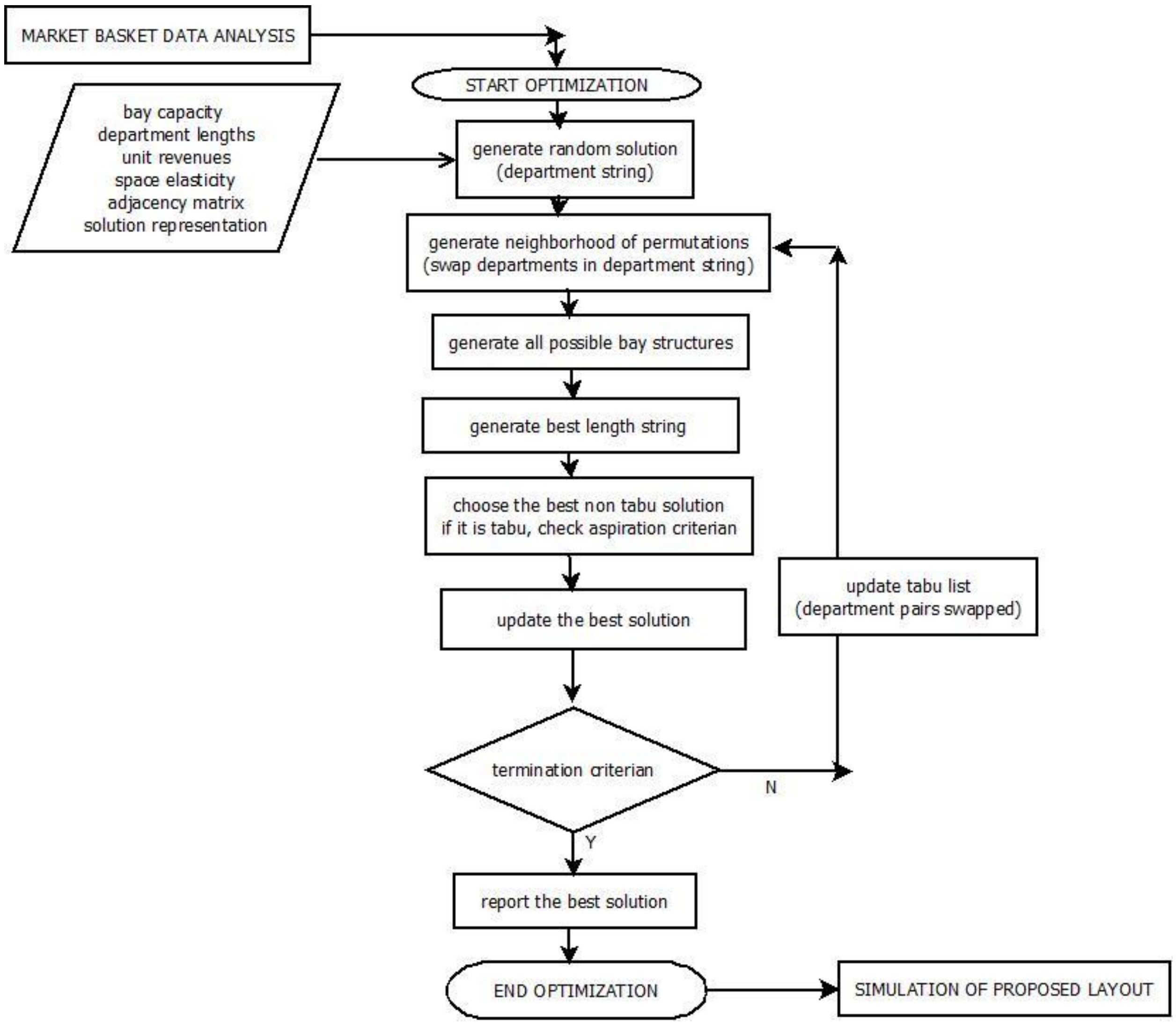

Figure 6.5 Overall Optimization Procedure

6.6 Experimentation

According to the data supplied by Migros, the algorithm (coded in Matlab) runs with the following parameters:

Experiment 1: As an initial experiment, use a fixed number of tabu tenure (10) and chose 500 iterations as the termination criterion. We tested the algorithm by using different initial seeds. The results are given in Table 6.5. For instance, in experiment 4, seed 12345 is chosen as an initial seed and the total revenue of the obtained layout is calculated from the deterministic equation in the TS is 128,824TL/day.

1	seed444	128,824
2	seed1	129,568
3	seed100	128,824
4	seed12345	128,824
5	seed10000	129,568
6	seed9999	131,130
7	seed500	131,130
8	seed650	129,568
9	seed223	131,130
10	seed36	131,130

Table 6.5 The results of the single objective TS for 10 different initial solutions (Tabu tenure=10 and termination criteria=500 iterations)

At the end of 10 runs, three different best layouts were found. The highest revenue calculated from the linear equation in the TS is 131,130TL/day and out of 10, the TS reached this value four times. The best layout is shown in Figure 6.6.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	4	5	6	7	8	9	10	10	11	11
2	4	12	14	18	21	1	15	17	5	23	22	20	9	16	13	8	24	7	10	19	6	25	3	11
16	11	6	18	6	7	22	24	22	28	19	19	6	13	12	7	19	19	19	19	19	13	6	10	9

Table 6.6 Solution found by the single objective TS Algorithm

The total revenue of the layout equals 131,130TL/day and the adjacency score equals 0.45.

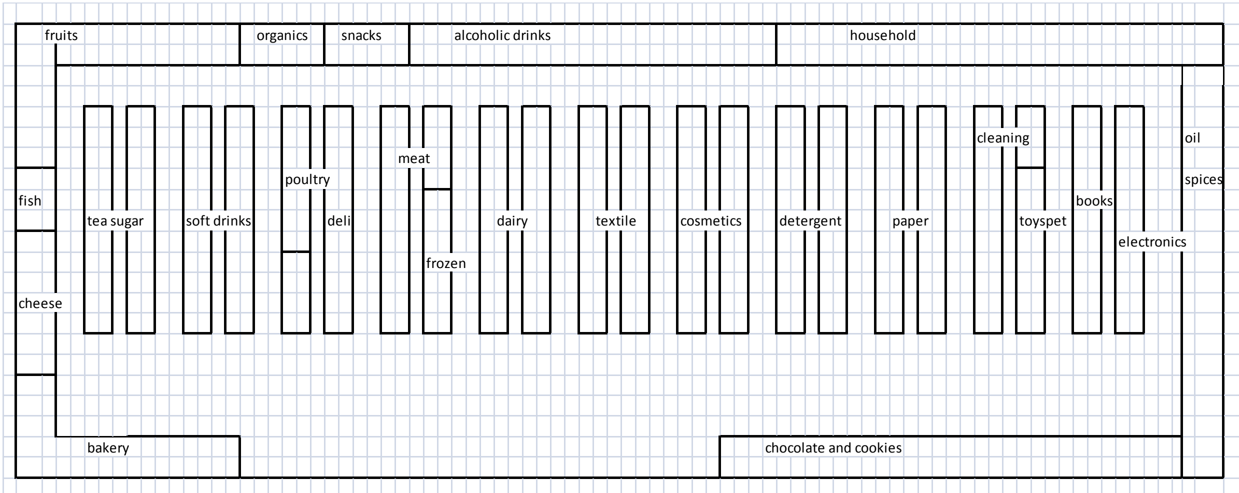

Figure 6.6 Proposed Layout 1of TS Algorithm

Experiment 2: As a second step, tabu size changes dynamically between (15, 30), and the new termination criteria also records non-improving moves and after 50 non-improving moves, the search terminates. We tested the algorithm for the new parameters for 10 different initial seeds. The results are shown in Table 6.7. The highest total revenue obtained from TS did not change but the new parameters have a positive effect on the results. The algorithm reached the highest total revenue six times out of 10. As we compare the Table 6.5 and Table 6.7, for the same initial seed, seed 444, the total revenue improved from 128,824TL/day to 131,130TL/day.

No	Initial Solution	Total Revenue
1	seed444	131,130
2	seed1	129,568
3	seed100	129,568
4	seed12345	128,824
5	seed10000	131,130
6	seed9999	129,568
7	seed500	131,130
8	seed650	131,130
9	seed223	131,130
10	seed36	131,130

Table 6.7 The new results of the single objective TS for 10 different initial solutions

An alternative layout with the same total revenue but with a 0.40 adjacency score obtained from this search is given in Table 6.8

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	4	5	6	7	8	9	10	10	11	11
1	4	18	14	12	21	17	15	2	5	23	22	20	9	16	13	8	24	7	10	19	6	25	3	11
22	11	6	18	6	7	22	24	16	28	19	19	6	13	12	7	19	19	19	19	19	13	6	10	9

Table 6.8 Alternative Solution found by the TS Algorithm with dynamic tabu size

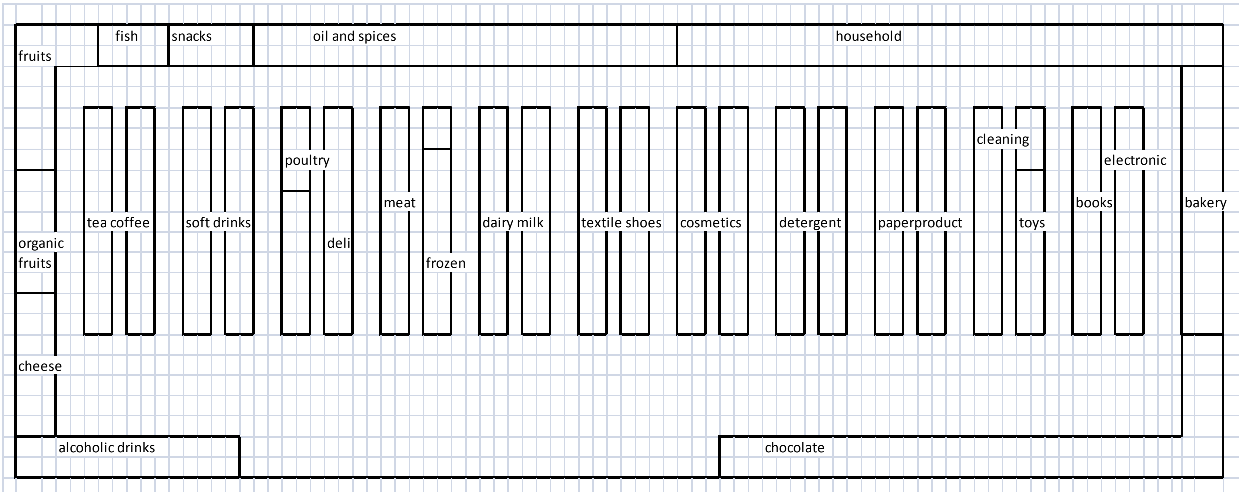

Figure 6.7 Proposed Layout 2 of TS Algorithm

In this chapter, we assumed revenue behaves linearly, that is, increasing or decreasing the length of departments affects the revenue function in a linear way. An increase in demand does not, however, directly relate to an increase in shelf space (Yapicioglu, 2008). Brown and Tucker (1961) show the law of diminishing marginal returns applies to the space/revenue relationship in retail settings. In the literature, “the ratio of sales to space is positive although its size decreases as space increases” (e.g., Brown and Tucker 1961; Bultez and Naert1988; Eisend 2014). “The reason for this non-linear relationship is that there is a limit to sales determined by the maximum need of the consumers. Hence, increasing space does not linearly lead to more sales, but only up to a certain limit” (Eisend, 2014). A new non-linear revenue function considering shelf space elasticities appears in detail in Section 6.7.

6.7. Shelf Space Allocation and Revenue Function

Although this dissertation has proposed a solution method for the block layout problem, one should also consider shelf space allocation models in the optimization stage of space and revenue. Since the shelf space allocated to an item influences the item's sales, the revenue function should consider the space elasticity of product categories.

Space elasticity amounts to "the ratio of relative change in unit sales to relative change in shelf space" (Curhan, 1972) - the ratio of additional sales to additional space allocated in retail settings. "The relationship between shelf space change and elasticity is very important because it provides information on differences in consumer reactions and how to change shelf space devoted to a product or category in order to enhance sales" (Eisend, 2014).

Similar to shelf space allocation models, the model proposed in this dissertation uses diminishing returns in revenue with respect to length. Motivated by Irion et al. (2004), Yapicioglu (2008) defines the revenue of department of a department as follows:

$$R_{i}=r_i\, A_i^{\beta i} \tag{6.1}$$

In our problem, departments have upper and lower bounds on shelf space similar to Yang's Model (2001), so the revenue function is defined as below:

$$R_{i}=r_i\, s_i^L + r_i(s_i - s_i^L)^{\beta i} \tag{6.2}$$

$$s_i^L \leq s_i \leq s_i^U \tag{6.3}$$

r_i: unit revenue for department *i*

β_i: space elasticity for department *i*

s_i : shelf space allocated to department *i*

Shelf space elasticity is assumed to depend on characteristics of the product, the store, the direction and amount of the variation of shelf space (Eisend, 2014). In the literature of estimations of shelf space elasticities, most studies analyze experiments. These include Curhan (1972), Bultez and Naert (1988) and Dreze et al. (1994). In a large-scale study, Curhan (1972) observed unit sales of about 500 grocery products in four stores during five to twelve weeks before and after changes in shelf space. The average shelf-space-elasticity estimate is 0.21.

Bultez and Naert (1988) create an optimization method called *S.H.A.R.P.* (Shelf Allocation for Retailer Profit) and optimized space allocation within a product category, taking into account interdependencies within product groups and across groups using marginal analysis approach. For a milk drink product category in the Netherlands their average shelf space elasticity is 0.30. Dreze et al. (1994) conduct experiments to study several shelf design aspects. The results from these experiments suggest that brand-level shelf space elasticity is between zero and 0.50, with a mean around 0.20. Another study by Thurik (1988) searches the space elasticity at store level and draws the conclusion that it is 0.68 for supermarkets and 0.51 for hypermarkets.

Desmet and Renaudin (1998), examine data from more than 200 stores belonging to same French store chain. The database includes a year of monthly sales and space data by category. The product categories include food products such as drinks with 0.39 space elasticity, fruit and vegetables with 0.57 space elasticity, and household products with 0.17 space elasticity. Figure 6.8 shows the space elasticities for each product category; varying from -0.44 to 0.80. All 25 product categories of Migros Store do not, however, appear in the list.

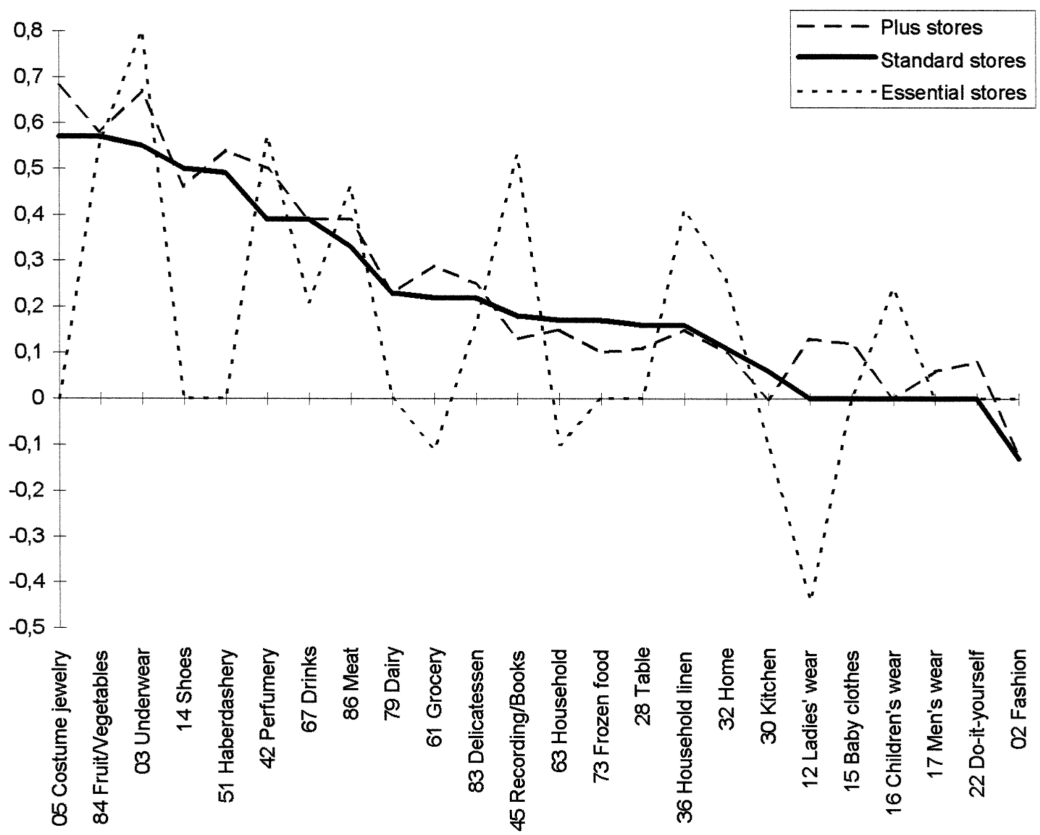

Figure 6.8 Space elasticities of product categories for three types of stores (Source: Desmet and Renaudin, 1998)

Irion et al. (2004) suggest intervals of space elasticity for three categories based on interviews with store managers- [0.06, 0.1] for unresponsive products, [0.16, 0.20] for moderately responsive products, and [0.21, 0.25] for responsive products. Van Dijk et al. (2004) use data for five brands of the shampoo category in the Netherlands. These brands account for 84 percent of total category sales. The scanner data provided by ACNielsen refer to 44 supermarkets from a large retailer, cover 109 weeks in 1995–1997, and include information about prices, promotional activities and sales; they found that the shelf space elasticity estimates range from 0.62 to 1.08 with an average of 0.85. To obtain valid estimates of shelf space elasticities for allocation decisions, they propose an approach that incorporates the spatial correlation between shelf space and the error term resulting from store, consumer and competitor characteristics.

In the light of the findings of previous research in shelf space elasticity, we estimated the space elasticity of each product category and tested the resulting revenue using formula 6.2. Knowing the current layout and the lengths, we reach the current total revenue by giving values to space elasticities of product categories in the equation.

$$TR = r_i s_i^L + r_i * (s_i - s_i^L)^{\beta i}$$

$$= 346*7+346*(9-7)^{0.75}+433*10+433*(13-10)^{0.95}+\ldots\ldots\ldots\ldots+259*7+259*(9-7)^{0.75}$$

121,000 ≈121,000TL

The space elasticities assumed for each product category in the Capitol Migros Store appear below:

PRODUCT CATEGORY	space elasticity(β)
ALCOHOLIC DRINKS and TOBACCO	0.95
BAKERY	0.95
BOOKS AND MAGAZINES	0.85
CHEESE OLIVES	0.95
CHOCOLATE AND COOKIES	0.95
CLEANING PRODUCTS	0.85
COSMETICS	0.95
DAIRY MILK YOGURT	0.95
DELI/SIDE DISH	0.95
DETERGENT	0.85
ELECTRONICS	0.75
FISH	0.65
FROZEN FOOD AND EGG	0.75
FRUITS AND VEGETABLES	0.95
HOUSEHOLD	0.85
MEAT SECTION	0.75
OIL AND SPICES	0.95
ORGANIC FRUIT AND VEGETABLES	0.45
PAPER PRODUCTS	0.95
POULTRY	0.45
SNACKSNUTS	0.85
SOFT DRINKS	0.85
TEA SUGAR CANNED FOOD BREAKFAST	0.95
TEXTILE AND SHOES	0.75
TOYS and PET	0.65

Table 6.9 Preliminary estimated space elasticity of product categories for Migros

As seen from the table above, the space elasticity of the Migros Store product categories varies between 0.45 and 0.95. Product categories with 0.95 space elasticity behave almost in a linear way; ones with 0.45 space elasticity, such as poultry or organic fruits, however, lie far from linearity. For a better understanding, starting from minimum length requirement to three times this length versus revenue graphs of some product categories appear in the figures below:

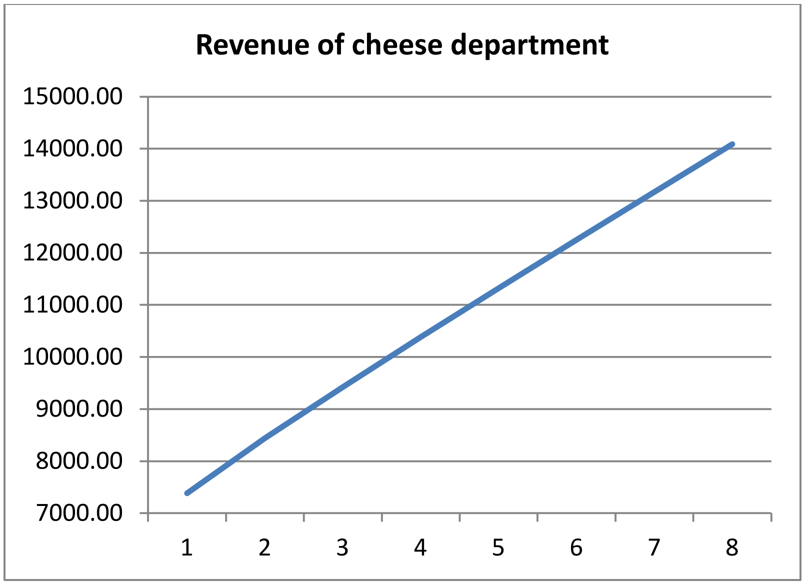

Figure 6.9 Space elasticity graph of the cheese department (space elasticity=0.95)

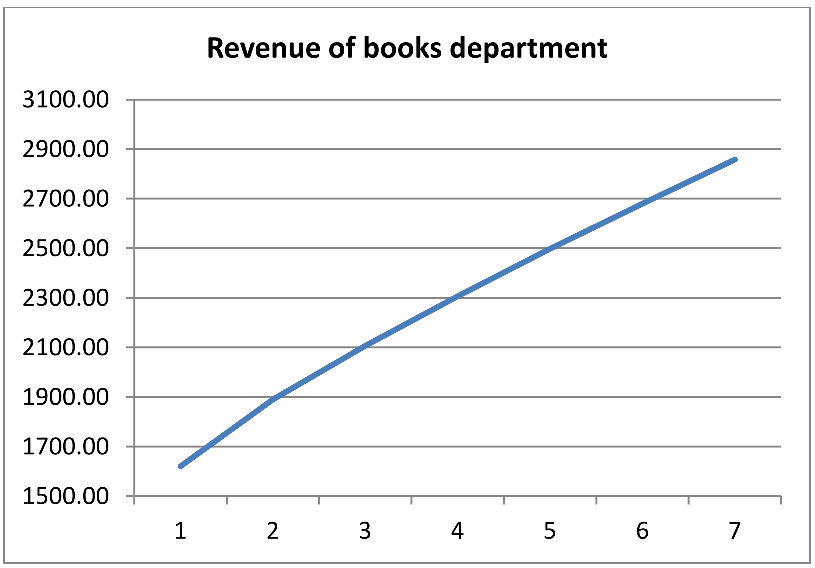

Figure 6.10 Space elasticity graph of the books department (space elasticity=0.85)

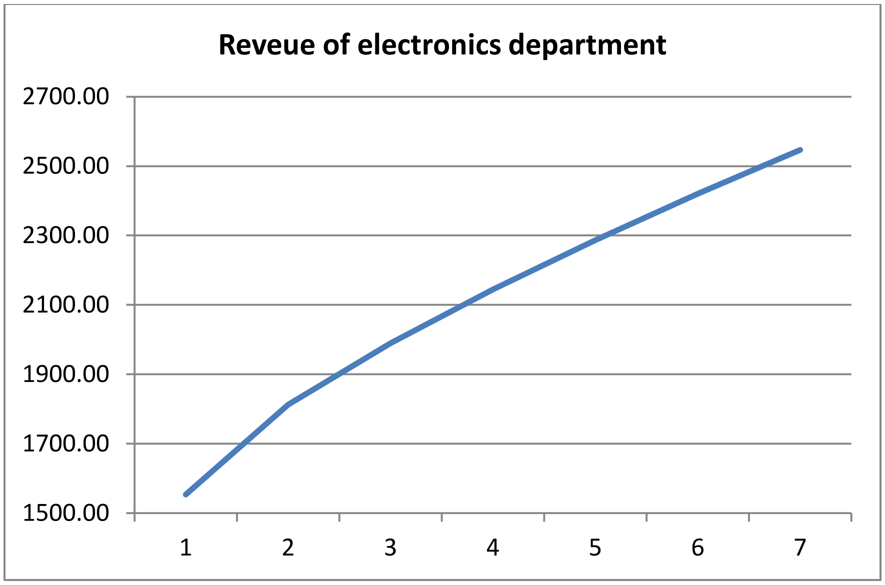

Figure 6.11 Space elasticity graph of the electronics department (space elasticity=0.75)

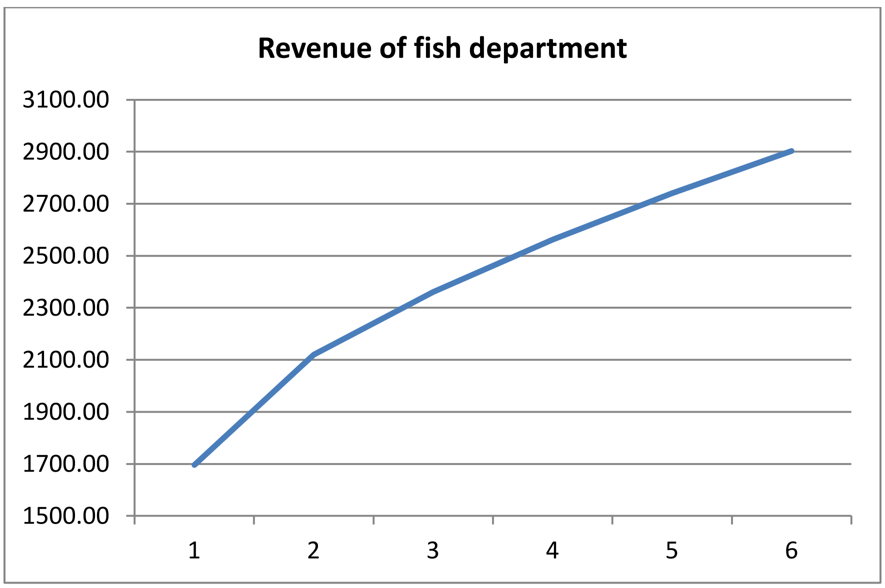

Figure 6.12 Space elasticity graph of the fish department (space elasticity=0.65)

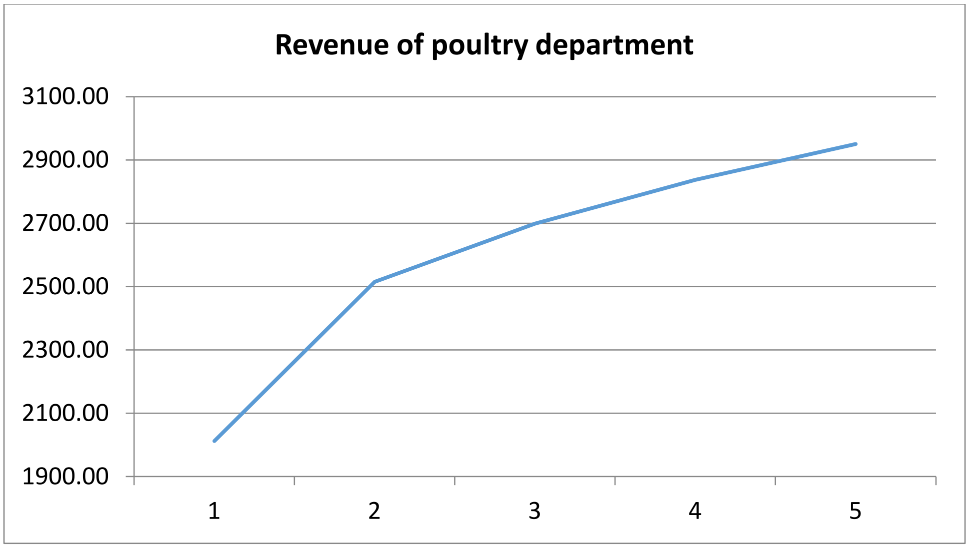

Figure 6.13 Space elasticity graph of the poultry department (space elasticity=0.45)

When we use the new revenue function considering space elasticities, the best solution found earlier with the TS algorithm does not change; in other words, the best layout is the same. The diminishing returns affect the total revenue, however, by decreasing the number. The total revenue for the best layout, now calculated as 126,915TL, assumes a totally linear model has 131,130TL. The algorithm is tested for new revenue function considering space elasticities for different initial solutions and the results are shown in Table 6.10.

No	Initial Solution	Total Revenue
1	seed444	126,915
2	seed1	125,145
3	seed100	125,145
4	seed12345	126,915
5	seed10000	126,915
6	seed9999	125,145
7	seed500	126,915
8	seed650	126,915
9	seed223	126,915
10	seed36	126,915

Table 6.10 The results of the single objective TS considering space elasticity for 10 different initial solutions

The total revenue is calculated in the TS by using the power model in Equation 6.2 and space elasticities in Table 6.9. TR $=r_i\, s_i^L {}_+ r_i \,*\, (s_i - s_i^L)^{\beta i}$ and summed over all departments.

$TR_{\text{Alcholic drinks}}$=731*14+(22-14)$^{0.95}$=15,504TL

TR_{Bakery}=433*10+(16-10)$^{0.95}$=6,705TL

The rest of the departments and their total revenue per day calculated by TS are shown below:

PRODUCT CATEGORY	TOTAL REVENUE
ALCOHOLIC DRINKS and TOBACCO	15504.5
BAKERY	6705.4
BOOKS AND MAGAZINES	2497.2
CHEESE OLIVES	11322.4
CHOCOLATE AND COOKIES	12622.0
CLEANING PRODUCTS	1542.9
COSMETICS	6327.0
DAIRY MILK YOGURT	5111.0
DELI/SIDE DISH	4485.0
DETERGENT	4416.3
ELECTRONICS	2144.4
FISH	2361.3
FROZEN FOOD AND EGG	2415.0
FRUITS AND VEGETABLES	9022.7
HOUSEHOLD	2640.0
MEAT SECTION	7287.5
OIL AND SPICES	3498.0
ORGANIC FRUIT AND VEGETABLES	2172.0
PAPER PRODUCTS	6049.4
POULTRY	2699.1
SNACKSNUTS	3013.5
SOFT DRINKS	3534.0
TEA SUGAR CANNED FOOD BREAKFAST	8189.9
TEXTILE AND SHOES	607.0
TOYS and PET	690.0

Table 6.11 Total Revenue per department per day calculated by the non-linear TS objective function

As seen from the Table 6.10 and Table 6.11, the total revenue obtained from the non-linear model is less than the total revenue obtained from the linear model. When the resultant layouts of two models compared, they are identical. In other words, space elasticity influences only the total revenue because of the diminishing returns effect. The optimization and the identified best layout are robust to assumptions about the form of the revenue to length elasticity equation, which is a positive aspect. We have to remember that these are the results of deterministic equations of TS. The best layout obtained is simulated and the revenue obtained from stochastic simulation is shown in Section 6.8.

Sensitivity analysis

Shelf space allocation models suffer from two important problems, which often limit their effectiveness. "First, because of non-linearities and complexities, the models must often be simplified before a solution set can be derived. Second, the number of parameters that must be estimated is large and estimation procedures introduce errors" (Borin and Farris, 1995). For this reason, sensitivity analysis must be examined for possible parameter estimation errors.

If we use another approach in space elasticity estimating, will the best layout change? Following Irion et al. (2004), some intervals of impulse purchase rate were assumed. These intervals were assigned corresponding space elasticities. As mentioned in the literature and in this paper, impulse buying rate has positive relationship with space elasticity so the defined intervals are as follows:

Impulse purchase rate	Space elasticity
1-2	0.17
3	0.39
4-5	0.57

Table 6.12 Space elasticities according to impulse purchase rate

For instance, the soft drinks department has 3 impulse rate and the space elasticity of 0.39. Alcoholic drinks, not included in the paper, have same impulse rate as soft drinks, so we assumed the space elasticity also as 0.39. The rest of the categories are not in the list were estimated in the same way. Table below gives the impulse rates and revised space elasticities of product categories of Migros store.

PRODUCT CATEGORY	IMPULSE RATE	SPACE ELASTICITY
ALCOHOLIC DRINKS and TOBACCO	3	0.39
BAKERY	5	0.57
BOOKS and MAGAZINES	3	0.39
CHEESE OLIVES	3	0.39
CHOCOLATE and COOKIES	5	0.57
CLEANING PRODUCTS	2	0.17
COSMETICS	5	0.57
DAIRY MILK YOGURT	4	0.57
DELI/SIDE DISH	4	0.57
DETERGENT	2	0.17
ELECTRONICS	1	0.17
FISH	3	0.39
FROZEN FOOD and EGG	1	0.17
FRUITS and VEGETABLES	4	0.57
HOUSEHOLD	2	0.17
MEAT SECTION	2	0.17
OIL and SPICES	4	0.57
ORGANIC FRUIT and VEGETABLES	1	0.17
PAPER PRODUCTS	2	0.17
POULTRY	2	0.17
SNACKNUTS	4	0.57
SOFT DRINKS	3	0.39
TEA SUGAR CANNED FOOD BREAKFAST	4	0.57
TEXTILE and SHOES	3	0.39
TOYS and PET	1	0.17

Table 6.13 Revised space elasticity of product categories in Migros Store

Using the space elasticities given in Table 6.13, the resultant layout maximizing the total revenue did not change, but with the new space elasticities, the total revenue is calculated as 111,443TL/day. According to these elasticities, if we calculate the current store revenue, it equals 110,646TL/day. The actual store revenue is 121,972 TL/day. This new revenue is less than the current store revenue. For our case, the space elasticity values we originally used perform better than the ones found in the literature for our test case of the Capitol Migros store. It is also mentioned in the literature that different countries can have different space elasticities. Since, the elasticities given in Table 6.9 give almost same results when compared to the actual store data, in the rest of the chapter, the TS calculates the total revenue according to the space elasticities given in Table 6.9.

No	Initial Solution	Total Revenue
1	seed444	111,443
2	seed1	111,071
3	seed100	110,819
4	seed12345	111,071
5	seed10000	111,443
6	seed9999	110,819
7	seed500	111,443
8	seed650	111,443
9	seed223	111,443
10	seed36	111,443

Table 6.14 The results of the single objective TS considering revised space elasticity for 10 different initial solutions

Even though the total revenue value is underestimated, the algorithm is tested for 10 different initial seeds with the revised space elasticities and the results are shown in Table 6.14. The best total revenue value obtained from TS is 111,443 TL/day but the best layout does not change from the previous TS runs. It is the same layout given in Figure 6.6.

6.8. Simulation of the Proposed Layouts

In this section, we feed the resultant layouts of constructive heuristic with constraint (see Figure 6.4) and the two layouts (see Figure 6.6 and Figure 6.7) found by using TS to the Simio Simulation discussed in Chapter 4. Using the same simulation settings, the total average revenue is 124,012TL/day for the constructive heuristic and for the TS 126,582TL/day and 126,385TL/day, respectively. These values are very close to the deterministic revenue using the space elasticities of the product categories. Table 6.15 gives the average revenue per product categories for the three proposed layouts using simulation.

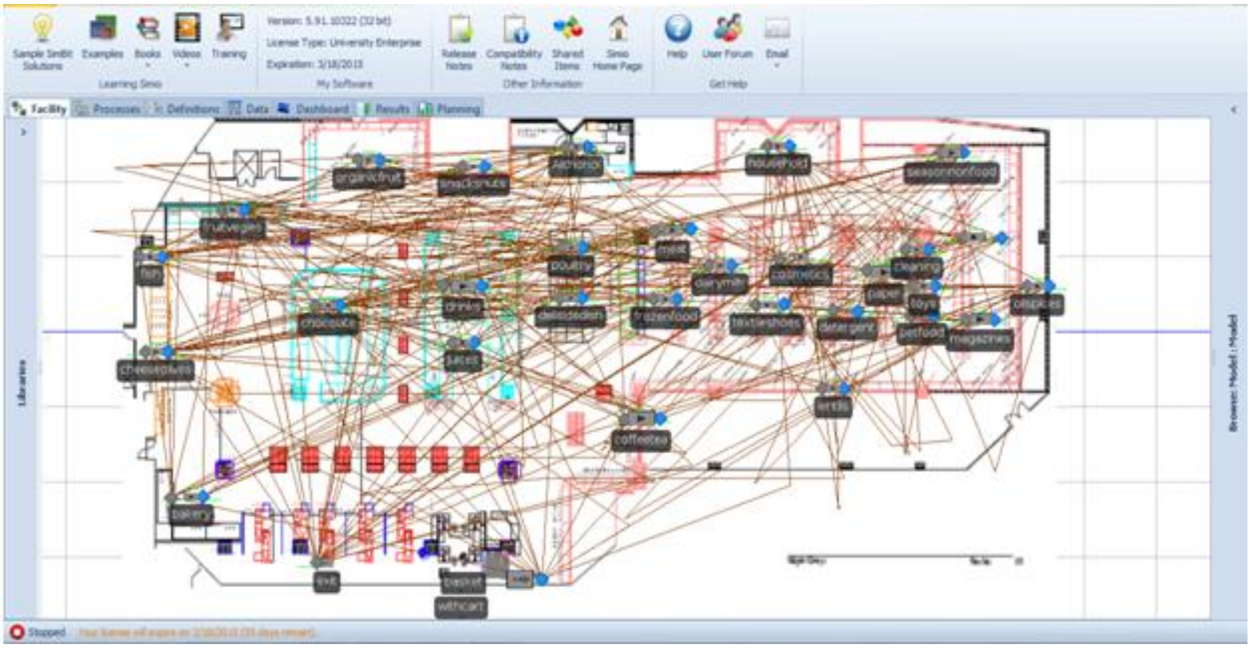

Figure 6.14 Simio representation of proposed layout of the constructive heuristic with constraint

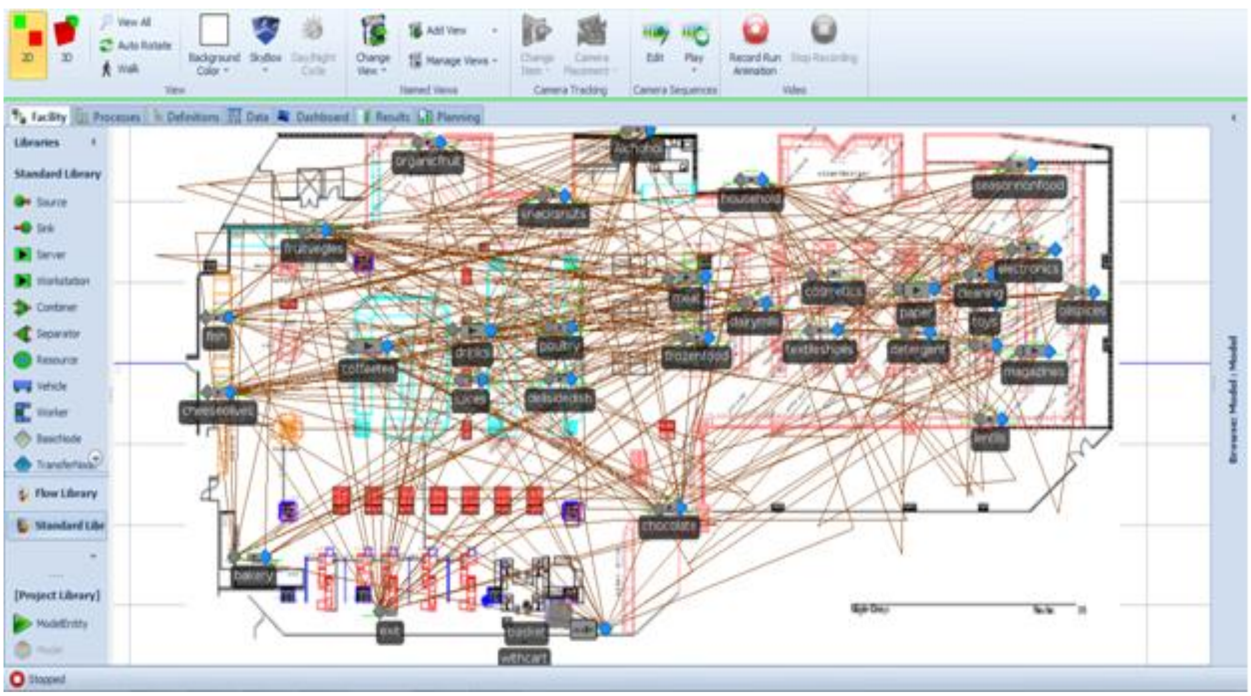
Figure 6.15 Simio representation of proposed layout 1of the TS

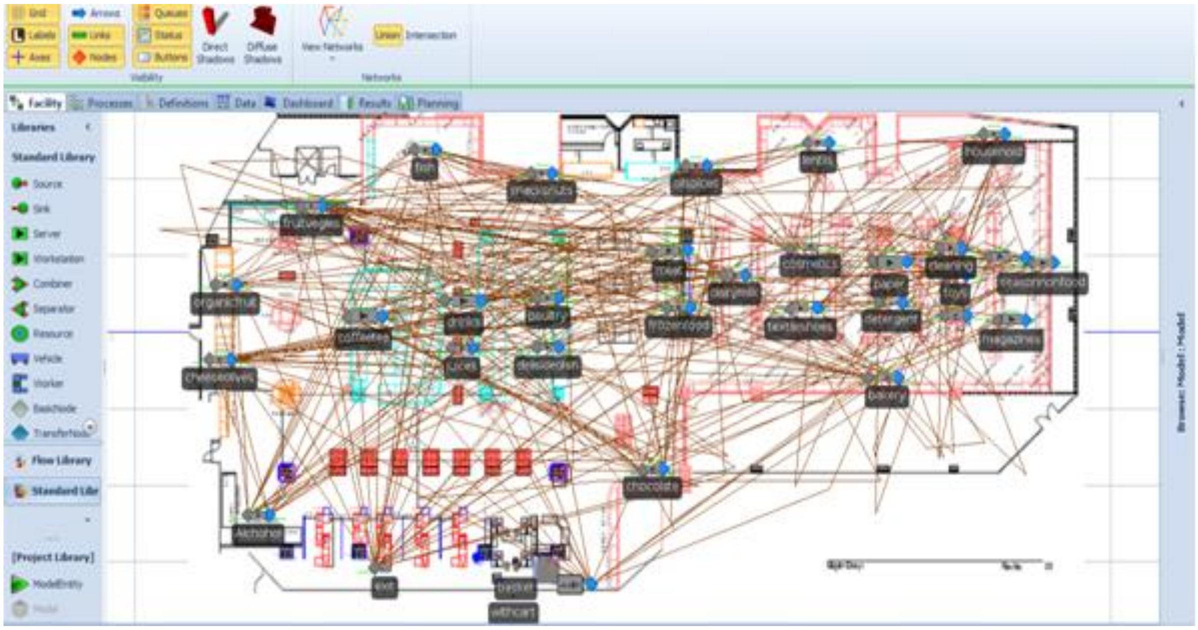

Figure 6.16 Simio representation of proposed layout 2 of the TS

PRODUCT CATEGORY	STORE VALUE	TR CONSTRUCTIVE	TR TABU 1	TR TABU 2
ALCOHOLIC DRINKS and TOBACCO	13,165.77	13,136.40	14,209.27	13,847.92
BAKERY	5,629.22	5,697.83	5,884.37	5,901.59
BOOKS and MAGAZINES	2,164.40	2,133.67	2,200.03	2,370.56
CHEESE OLIVES	9,500.07	8,948.99	9,446.49	9,289.65
CHOCOLATE and COOKIES	10,793.50	11,346.23	11,260.38	11,208.56
CLEANING PRODUCTS	1,606.84	1,825.29	1,705.20	1,849.38
COSMETICS	7,329.55	7,104.02	7,486.41	7,322.13
DAIRY MILK YOGURT	6,193.63	5,941.75	6,119.20	6,195.38
DELI/SIDE DISH	5,188.10	5,132.36	5,860.42	6,017.72
DETERGENT	4,602.05	4,769.46	4,642.74	4,769.43
ELECTRONICS	2,075.26	2,329.88	2,382.20	2,351.26
FISH	2,120.22	1,990.91	1,999.06	2,040.55
FROZEN FOOD and EGG	3,113.27	2,894.81	3,199.42	3,140.16
FRUIT and VEGETABLES	7,752.43	8,428.16	8,017.13	7,779.72
HOUSEHOLD (season nonfood)	3,323.67	3,389.46	3,262.05	3,489.04
MEAT SECTION	6,734.24	6,936.34	7,264.81	7,074.83
OIL and SPICES (beans and lentils)	4,307.47	4,693.97	4,383.27	4,302.36
ORGANIC FRUIT and VEGETABLES	2,173.00	2,064.24	2,071.29	2,251.08
PAPER PRODUCTS	5,863.68	6,094.43	6,075.46	6,351.69
POULTRY	2,518.21	3,190.53	3,130.12	3,004.02
SNACKSNUTS	2,660.95	2,691.13	2,871.94	2,849.40
SOFT DRINKS (juices)	4,108.07	3,832.57	3,911.64	3,874.31
TEA CANNED FOOD SUGAR BREAKFAST	7,481.34	7,741.13	7,528.14	7,346.96
TEXTILE and SHOES	644.42	826.34	774.02	788.62
TOYS and PET	923.00	872.92	897.83	968.92
	121,972.31	**124,012.80**	**126,582.92**	**126,385.23**

Table 6.15 Simulation Results of Each Layout

6.9. Bi-objective Model for the GSLP

In this dissertation, we initially modeled the GSLP with a single-objective function maximizing the total revenue under a constraint of adjacencies; the results show the conflicting structure of the revenue and adjacency. For instance, the TS algorithm increased the total revenue but the adjacency score of the best layout stayed in 0.45. The constructive heuristic has a 0.63 adjacency score but the total revenue equals less than the proposed layout of the TS. To find a more effective layout, we should consider both objectives; this motivates the bi-objective optimization approach.

Since Rosenblatt (1979), researchers have proposed a number of multi-objective approaches to the facility layout problem. "The purpose of multi-objective facility layout problems is to generate efficient alternatives which can then be presented to the decision-maker so that he/she can select the best facility layout alternative while considering conflicting and non-commensurate objectives" (Sahin and Turkbey, 2009). As we mentioned earlier, in today's world, consumer preferences and market conditions change rapidly. Furthermore, the decision maker's preferences can change over time. Therefore, instead of offering a single alternative, giving options and letting decision-maker choose among them based on the changing market conditions is more realistic and appropriate in facility layout problems (Sahin and Turkbey, 2009).

"A multi-objective solution that simultaneously optimizes each objective function is almost impossible. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution" (Kulturel-Konak et. al., 2006). Our study develops a Pareto-optimal set of solutions for a GSLP.

"A solution is called Pareto optimal if it is not possible to decrease the value of one objective without increasing the value of the other" (Jannat et. al., 2010). In other words, "a solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space" (Kulturel-Konak et. al., 2006). "The Pareto optimal set represents a trade-off between the objective functions, and it is impossible to say that one point is ‘‘better’’ than another without introducing preferences or relative weighting of the objectives” (Jaeggi et.al., 2008).

Researchers commonly use metaheuristic methods with FLP, usually modeled as a combinatorial optimization problem. According to the review of Jones et al. (2002), the most popular metaheuristics for FLP are genetic algorithms, simulated annealing and tabu search. In this study, multinomial tabu search (MTS) algorithm developed by Kulturel-Konak et al. (2006) will be used as a solution approach. The main difference between this approach and previous multi-objective tabu search algorithms is using a multinomial probability mass function to select the active objective function in each move; this eliminates the issue of weighting and scaling of each objective in other multi-objective tabu search approaches.

Objective Functions: The bi-criteria GSLP model considers two objective functions: maximizing total revenue (TR) and maximizing adjacency (ε).

F_{TR}: Total Revenue F_{ε} : Adjacency score

Similar to Kulturel-Konak et al. (2006) and Yapicioglu and Smith (2012), we choose the objective function at every iteration of the algorithm according to the respective probabilities of the objective functions. Therefore, we define p_{TR} and p_{ε} as the probabilities of using either F_{TR} or F_{ε} as the fitness function at a given iteration of the bi-objective tabu search ($p_{TR} + p_{\varepsilon} = 1$). For instance, if $p_{TR} = p_{\varepsilon} = 0.5$ is used, both objective functions are equally likely to be active at a given iteration of the search. We used different configurations of p_{TR} and p_{ε} are used to obtain the Pareto archive, but the number of non-dominated solutions found did not change.

p_{ε}	p_{TR}	No. of Pareto solutions
0.1	0.9	3
0.2	0.8	3
0.3	0.7	3
0.4	0.6	3
0.5	0.5	3

Table 6.16 Multinomial probability mass function settings

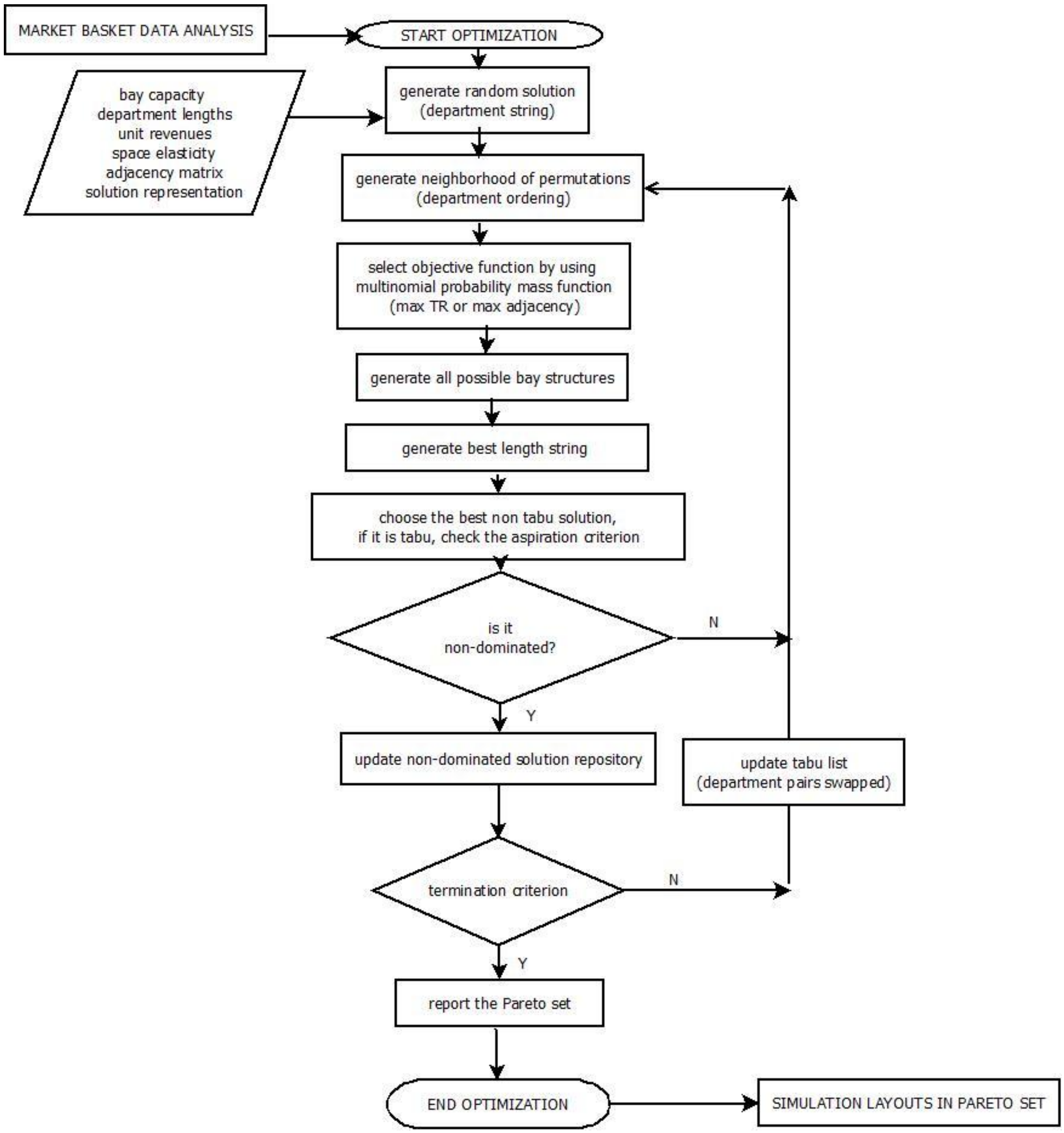

Figure 6.17 Overall procedure for multi-objective tabu search

We used the same encoding and neighborhood structure as with the single-objective TS algorithm and the same swap move operator. As the aspiration criteria, if a solution within the neighborhood dominates a solution from the set of non-dominated solutions, we allowed a move to that solution even if tabu. The tabu tenure dynamically changes with uniform probability between (15, 30). If no update is performed to the non-dominated solution set for 50 consecutive iterations, the search terminates.

The bi-objective algorithm is run for the same 10 seeds used in the single objective TS for $p_{TR} = p_{\varepsilon} = 0.5$ probability and the same three solutions in Figure 6.17 is obtained over all 10 seeds. The bi-objective model is less sensitive to the initial solution. The reason for this situation is the occasional switching of objective functions during the search serves as a diversification strategy.

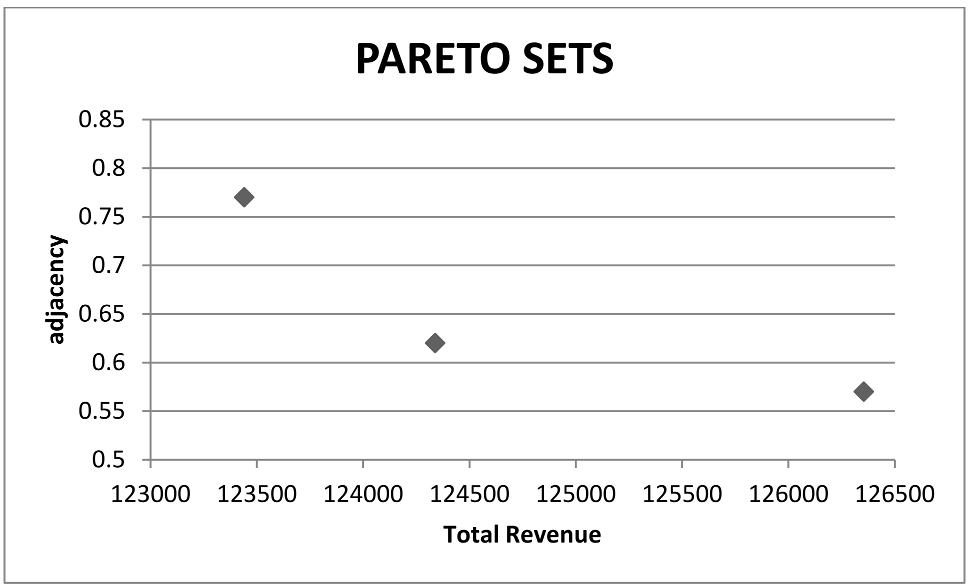

Figure 6.18 Pareto Archive

Figure 6.18 shows the pictorial representation of the Pareto archives obtained from five settings of the probability mass function. The best TR value (126,915TL/day) obtained from the single-objective TS is also found by the bi objective optimization. However, the adjacency score improved from 0.45 to 0.57 in the bi-objective optimization. The resultant layouts of the algorithm appear below:

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
2	4	18	14	12	15	17	21	1	5	23	22	20	9	8	13	16	24	7	19	10	6	25	3	11
16	11	6	18	6	24	22	7	22	28	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

Table 6.17 Solution with adjacency 0.57

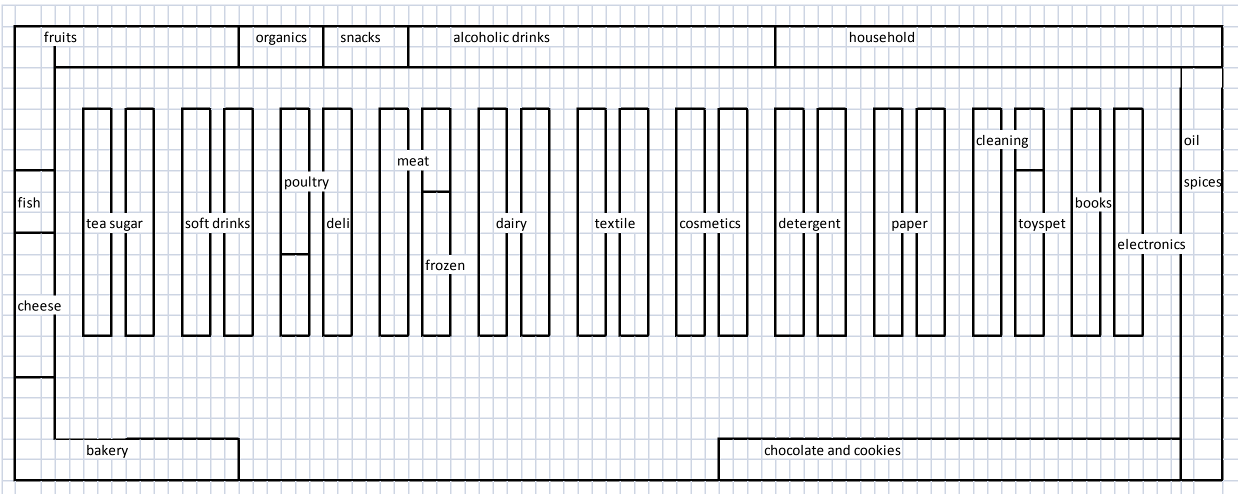

Figure 6.19 Single objective TS layout (adjacency=0.45)

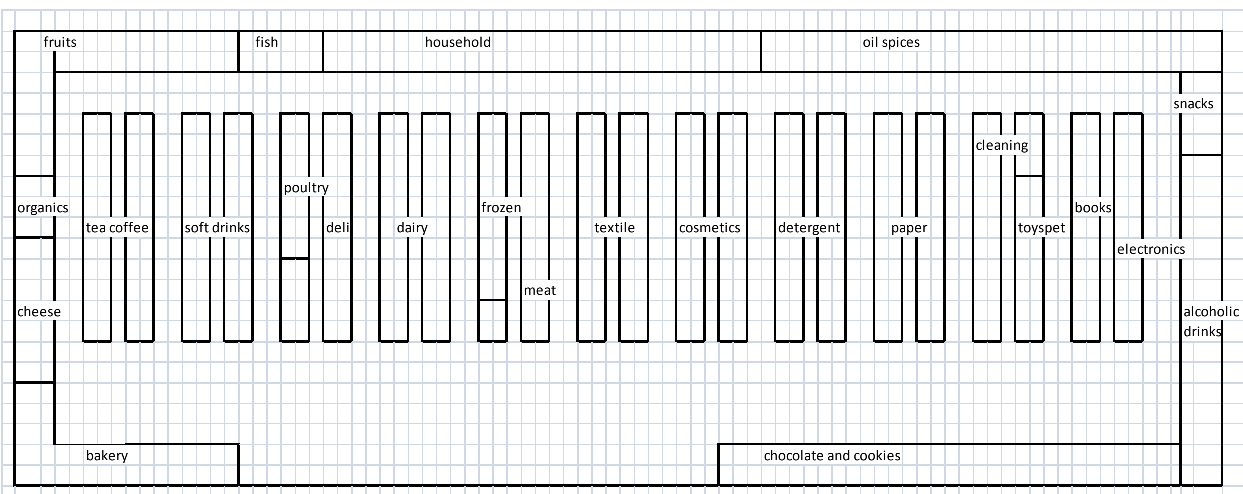

Figure 6.20 Single objective TS layout (adjacency= 0.57)

As seen from the figure, the location of household departments and the alcoholic drinks department changed in the racetrack aisle and the dairy department now comes between the deli and the frozen food departments in the grid part.

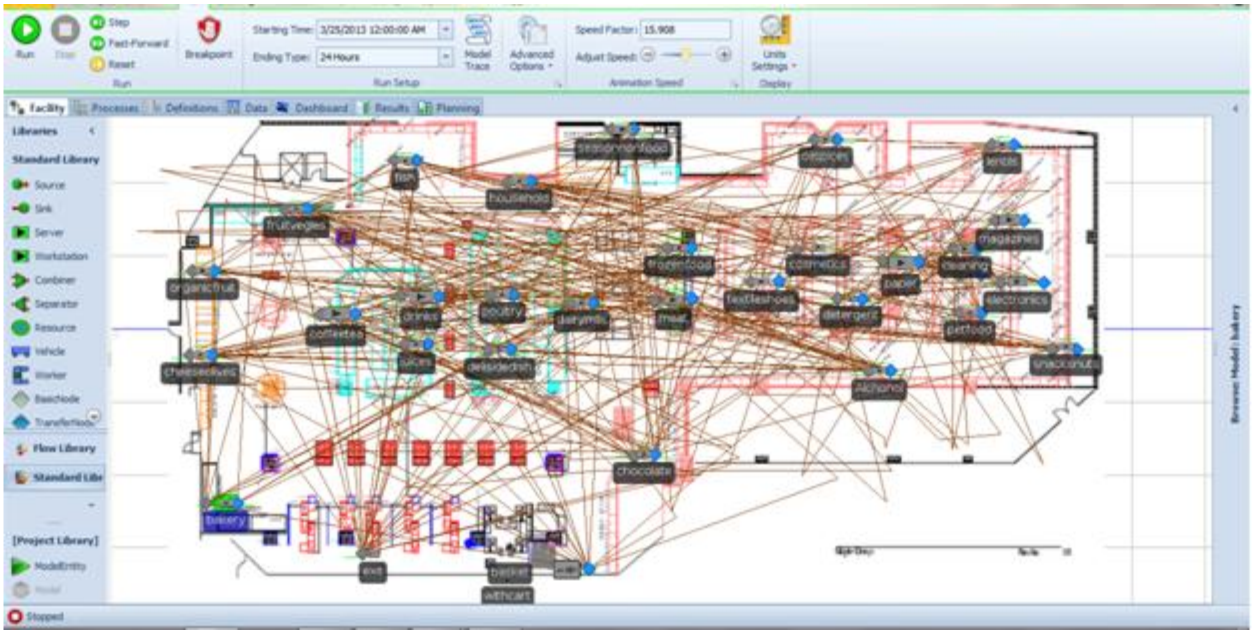

Figure 6.21 Simio representation of the layout with 0.57 adjacency.

The layout with the highest adjacency score appears in Table 6.18. The average total revenue calculated in TS equals 124,735TL/day and the Simio representation is illustrated in Figure 6.21. According to the simulation, the average total revenue is 124,620TL/day.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
2	4	23	17	15	18	14	12	1	21	22	5	20	9	8	13	16	24	7	19	10	6	25	3	11
16	11	20	29	24	7	18	6	22	7	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

Table 6.18 Solution with adjacency=0.77

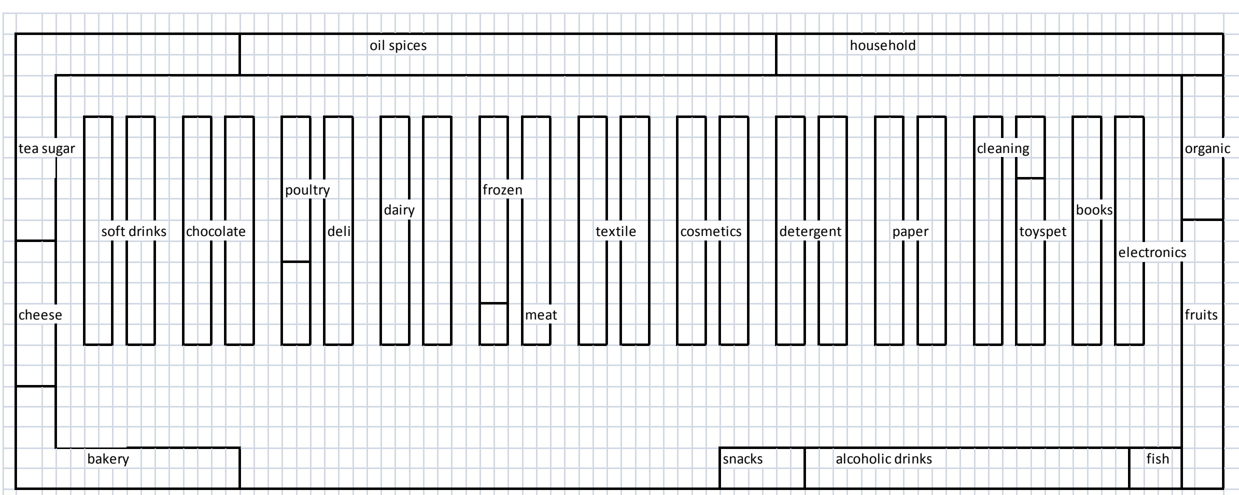

Figure 6.22 Layout with adjacency=0.77

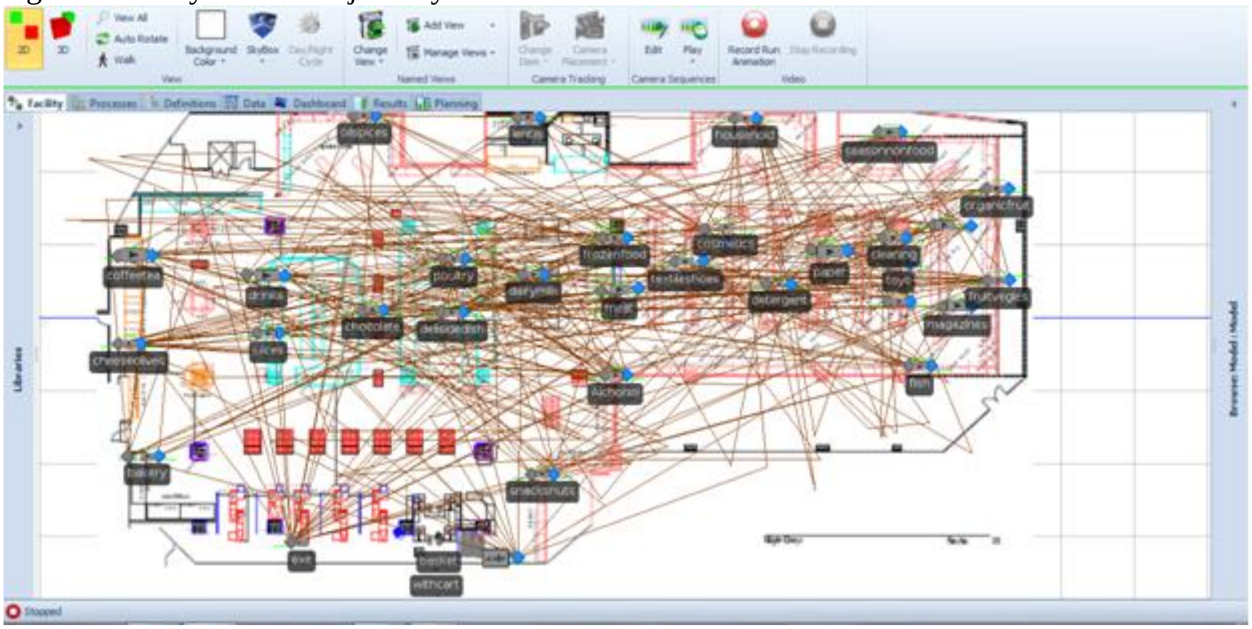

Figure 6.23 Simio Representation of Layout with 0.77 adjacency

A non-dominated layout with 0.62 adjacency and average total revenue 125,145TL is shown in Table 6.19. According to the simulation, the total revenue is calculated as 125,453TL.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
13	17	23	4	2	15	14	12	21	1	22	5	20	9	8	18	16	24	7	19	10	6	25	3	11
11	25	20	11	16	24	18	6	7	22	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

Table 6.19 Solution with adjacency=0.62

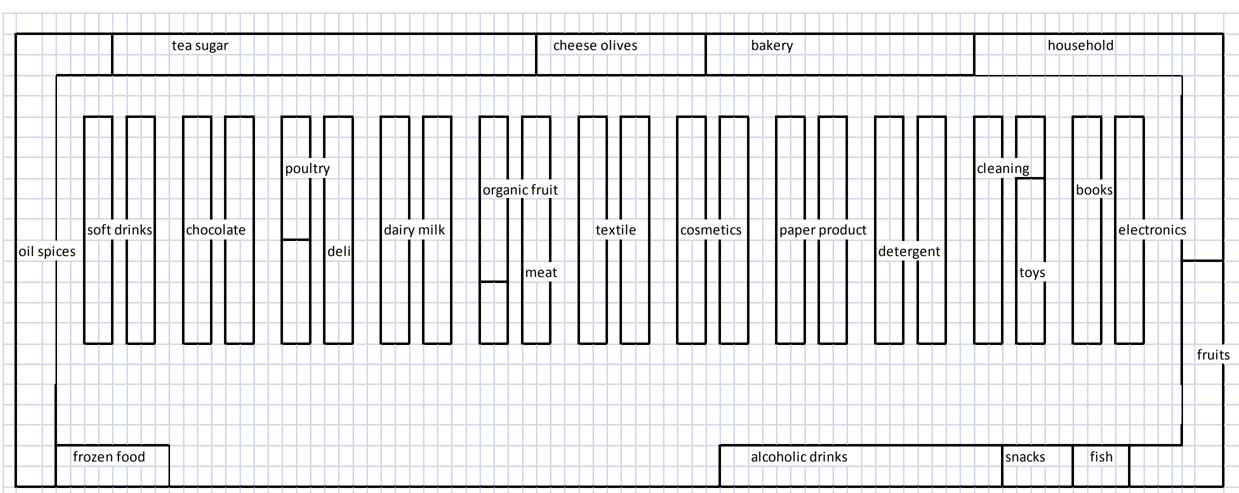

Figure 6.24 Layout 3 (adjacency=0.62)

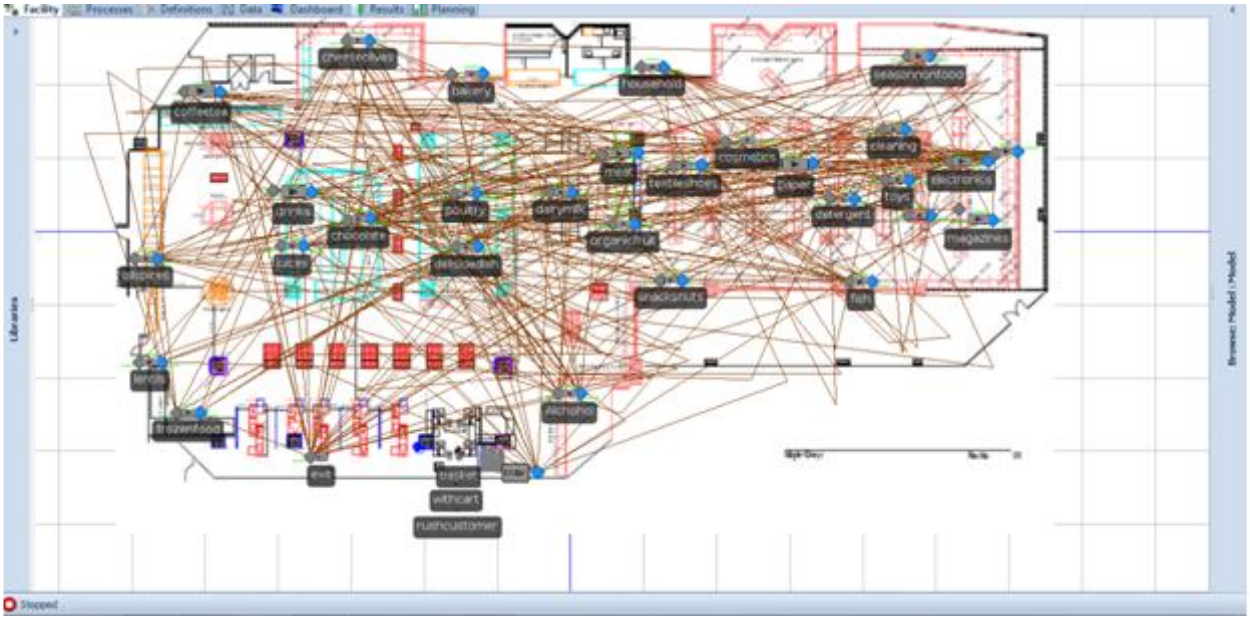

Figure 6.25 Simio representation of layout with 0.62 adjacency

PRODUCT CATEGORY	adjacency=0.57	adjacency=0.62	adjacency=0.77
ALCOHOLIC DRINKS and TOBACCO	13,276.27	12,967.28	13,427.81
BAKERY	5,884.81	6,103.66	5,762.18
BOOKS and MAGAZINES	2,353.45	2,182.61	2,169.91
CHEESE OLIVES	8,902.76	9,757.10	9,987.06
CHOCOLATE and COOKIES	12,261.09	10,391.19	11,402.78
CLEANING PRODUCTS	1,796.11	1,875.03	1,664.95
COSMETICS	7,683.93	7,364.34	7,202.95
DAIRY MILK YOGURT	6,231.56	6,254.01	6,061.78
DELI/SIDE DISH	5,821.14	5,908.11	5,706.84
DETERGENT	4,647.17	4,634.72	4,685.37
ELECTRONICS	2,211.85	2,445.84	2,348.38
FISH	2,093.05	2,015.27	2,016.00
FROZEN FOOD and EGG	3,012.64	3,176.86	2,835.85
FRUIT and VEGETABLES	8,018.84	8,017.13	8,059.24
HOUSEHOLD (season nonfood)	3,303.85	3,382.42	3,362.57
MEAT SECTION	7,131.87	7,133.69	6,884.74
OIL and SPICES (beans and lentils)	4,227.93	4,289.59	4,355.85
ORGANIC FRUIT and VEGETABLES	2,236.99	2,256.66	2,245.13
PAPER PRODUCTS	6,171.96	6,624.54	6,051.44
POULTRY	3,257.26	3,293.29	3,028.56
SNACKSNUTS	2,815.95	2,674.17	2,586.01
SOFT DRINKS (juices)	3,896.30	3,870.75	3,596.24
TEA CANNED FOOD SUGAR BREAKFAST	7,908.98	7,084.42	7,486.57
TEXTILE and SHOES	726.57	774.68	802.03
TOYS and PET	950.01	946.12	889.77
	126,822.31	**125,423.48**	**124,620.01**

Table 6.20 Summary of simulated revenue

As seen from the cases, a trade-off occurs between increased revenue and improved adjacency. Among the Pareto efficient solutions, the decision-maker should choose the best solution, but perhaps a good choice might involve the layout with the largest TR just before a significant decrease in adjacency. In our Pareto archive, the middle solution may not be a good option since the adjacency score of the maximum revenue layout and middle solution are almost same. As a conclusion, the results show using a bi-objective formulation has advantages over the single-objective formulation because one can identify solutions compromising high revenues with desired adjacency.

Chapter 7

Conclusions and Future Research

7.1. Conclusions

The retail industry has several important distinctions from the manufacturing industry. The success of retail layout depends on not only retailer considerations, but also customer satisfaction. This means the design must take into account not only quantitative factors, but also qualitative ones from a customer's perspective. This research proposes a model and solution approach for the grocery store block layout problem. The model maximizes revenue generated by choosing a store's departmental locations and sizing the departments within pre-specified bounds. Desired adjacencies and impulse purchase likelihoods are considered. This study addresses facility design in the retail industry with the participation of Migros, Turkey's largest retailer and the first truly organized food retailer. The data in the test case comes from the Capitol Migros Store in Istanbul.

The following summarizes the project:

- Characterization of the current store layout with stochastic simulation considering impulse purchase rates and customer traffic patterns;
- Identifying consumer buying habits by market basket analysis and using the analysis results in encouraging placing related departments next to each other;
- Modeling of the block layout optimization problem considering limited space requirements, unit revenue and department adjacencies. This model specifies department locations and exact sizes.
- Optimization of the model with two simple constructive heuristics and with both single objective and bi-objective tabu search. These optimization approaches use a deterministic surrogate for the stochastic simulation in evaluating revenue to ease the computational burden.
- Fully evaluating resultant layouts from the optimization approaches using discrete event stochastic simulation.

As an initial step, for better understanding of the current system, we generated a stochastic simulation model. The simulation model evaluates a layout by forecasting the total revenue of the store and each department. In this part, we added the human view by asking experienced store managers to rate impulse purchase likelihoods.

Next, for better understanding of consumer preferences and inter-relationships between product categories, we performed a market basket data analysis. The Migros Customer Relations Management (CRM) department receives transaction data, and, from the findings of affinity analysis, we developed an adjacency matrix used in the optimization stage. Retailers must put items routinely purchased together close to each other, not only to increase sales, but also to improve customers' shopping experiences.

Another essential aspect of this dissertation is shelf space elasticity. Since shelf space allocated to an item influences the item's sale, the revenue function should consider the space elasticity of product categories. Similar to the shelf space allocation models, this dissertation's proposed model uses diminishing returns in revenue with respect to length.

In the second part, optimization is used by considering limited space requirements, unit revenue production and department adjacencies. As an optimization tool, we proposed two simple constructive heuristic methods, and evaluated the resultant layouts in stochastic simulation. The total revenue calculated in TS and constructive heuristic are compared with the stochastic simulation's total revenue result. They provided satisfactory revenue and adjacency scores. Since we worked on a real case study, however, we did not have any comparison data, except the current layout. So, we also questioned whether we could have a better approach than the constructive heuristics.

Because of the strong neighborhood structure and complexity of the problem, we chose Tabu Search (TS) as a solution approach for this dissertation. Although tabu search does not guarantee optimality, it finds successful application with many combinatorial optimization problems. The final layout(s) generated in this step are evaluated by discrete event stochastic simulation and compared with the constructive heuristic results. The final layouts obtained from

TS have higher total revenue compared to the constructive heuristic layouts but the adjacency score of the layout obtained from constructive heuristic is better than TS layout.

As we have multiple objectives to maximize, a bi-objective model is formulated for the store with the concurrent objectives of revenue maximization and adjacency satisfaction. The proposed model gives decision-makers a restricted number of solutions from which to choose. A set of non-dominated designs was fully evaluated in stochastic simulation. This approach is both effective and pragmatic for optimal design of grocery store block layouts because it identifies solutions with high revenues and desired adjacency.

There are also some limitations of this study that should be mentioned. Since it is one of first studies that considers block layout for a real grocery store, during the simulation stage, we made assumptions regarding the three customer types and routings of the customers which are based on a shortest path algorithm. These assumptions are made because of the simplicity and can be modified in future studies. For instance, instead of a shortest path algorithm, another algorithm can be used to indicate some longer paths of customers.

Furthermore, the results of this study might be limited because when the layout of the Migros Capitol store is considered, we assumed a slightly different layout than the physical store. The total shelf length of the store model is the same as the physical store but the grid aisles are all the same length, which is not true in the physical store. In most grocery stores, even though retailers try to keep them equal; in practice they may be slightly longer or shorter than each other.

Finally, we should mention that the results of this project, both in the simulation part and the optimization part, could be better validated. Stronger validations could be accomplished by a detailed and large observational study and/or a detailed and large survey study. If there is the opportunity for a Migros 2M store to implement the recommended layout (or parts of it), then we could observe the actual results of the new design in terms of total revenue and customer satisfaction.

7.2. Future Research

As one of the first studies proposing a layout design of grocery stores considering impulse purchase rates, departmental adjacency, and space constraints, many ways to extend and to improve the model exist. First of all, we considered a block layout problem for grocery stores, with the main product categories taken into account. An extension opportunity would combine block layout with the shelf space allocation problem, considering detailed product placement and sizing in the store along with departmental placement and sizing.

Another research opportunity could involve solving the problem with different meta-heuristics, such as simulated annealing, genetic algorithms or ant colony optimization. A tabu search algorithm could compare the results to give a better understanding of the approaches' efficiency.

As time passes, technology improves and consumers have new demands, such as virtual shopping. The number of internet users increases every day, and customers, especially with long working hours, prefer to shop online. This research could extend to designing online grocery stores and comparing the results of virtual stores with conventional stores.

This model seeks total revenue maximization and adjacency satisfaction. Previous literature in marketing states a positive relationship exists between travel distance and unplanned purchase amounts, so future studies could add another objective, such as maximizing travel distance, to the model. Related to this is that we used the shortest path for a customer's routing through the store. In reality, not every customer uses the shortest path. More sophisticated pathing mechanisms in the simulation could be developed and tested. It would also be beneficial to get more actual data on how customers move through a grocery store.

As one of the first studies proposing an algorithmic approach to a grocery store layout problem, future studies will need to explore the method's usefulness. For example, using grocery stores in other countries or ones in more rural locations instead of a city center. Also, different sizes of stores may impact results. We have studied a medium sized store but might consider a hypermarket which is much larger.

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