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ORIGINAL PAPER

# A decision support approach to achieve competitive advantage for a hypermarket chain

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## Abstract

This paper describes the decision support approach used in the development process of the S Group's Prisma hypermarket chain in Finland. The management was looking for a new and sustainable operating model for the rapidly growing chain, and contacted the author to consult in the process. Fierce competition forced the search for new business ideas, tools and methods that would provide a clear competitive advantage. To find new perspectives, we decided to use statistical approaches and various decision support system options, such as multi-criteria modelling. A database was available for research and analysis, including data on purchasing behavior and key performance indicators (KPI). The approach had to take into account the role and impact of customers. It was highly important to include customer behavior in the analysis using shopping basket data. Shopping basket data was central in the current paper. From these, an observation matrix was created combining shopping basket data, product data and customer background information. Using multivariate methods, customer groupings and profiles were created with the data from the observation matrix. Using the customer profile and KPI data, a multi-criteria decision support system was produced to support strategic planning. The decision support system (DSS) model was created together with a market chain operational expert and an external methodological expert. We used the VIG software package developed by Korhonen (Belg J Oper Res Stat Comput Sci 27(3):15, 1987) to solve the problem because it is easy to use and requires no prior knowledge of computers or multi-objective linear programming models. Pareto Race plays a central role in the VIG system. The chain expert easily learned how to use and work with the model. The results were immediately visible and could be used to examine alternatives and assess their appropriateness. It was decided to present five different scenarios to the hypermarket chain management. The main objective of the development process was to develop a strategy that would provide the Prisma hypermarket chain with a long-term competitive advantage. Various models were developed and used to support the strategy work by analysing and exploring the data collected, prioritising and selecting decision options. Two currently retired managers (Mönkkönen, S Group, the chain manager, Prisma chain, Interview 02.06.2021, 2021), who were

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involved in the development process, rated the strategy process as very successful and the modelling carried out during the process significantly supported decision-making. The immediate help of DSS modelling for decision making comes from being able to provide decision makers with reasonable, better solution options to support their decision making. The final impact of decisions could be evaluated after a longer period of time, which in the case of the Prisma development project results means several comparable financial years. Finland suffered exceptionally badly from the financial crisis and the global economic downturn in 2008–2009. The Prisma chain has survived the periods and crises described above without any loss-making years, and the whole chain has grown from 16 units in 1992 to 68 units in 2020.

**Keywords** Customer analysis · Multiple objective linear programming · Performance improvement · Retail · Hypermarket · Multivariate analysis · Shopping basket analysis

**Mathematics Subject Classification** 90–10

## 1 Introduction

This paper describes the decision support approach (DSA) and modelling used in the S Group's Prisma hypermarket chain in Finland (see Sect. 2). The described decision support system (DSS) is part of an extensive development process that began in the 90 s that helped the Prisma chain to become the largest hypermarket chain in Finland (Finnish Grocery Trade 2005–2006).

Hypermarket chains entered the Finnish market in the beginning of early 1990s. New business ideas and ways of working had to be developed for them. The Prisma chain was a pioneer in this development in Finland and, right from the start, created a significant market position in competition between chains with its new business ideas. In 2019, Finland had 157 hypermarket-sized units in three different chains, the largest of which was Prisma with a 15.9% market share of the total grocery market (Finnish Grocery Trade 2020).

The Finnish grocery trade underwent a major structural change between 1995 and 2013. Finland joined the European Union in 1995 and its economy became increasingly integrated with the economies of EU countries. Finland joined the common Euro currency of the EMU countries in 2002. The grocery trade was concentrated in urban areas, where 43% of Finland's grocery stores were located, 53% of Finland's groceries were sold and 54% of the population lived in 2003 (Nielsen 2009).

Finland was exceptionally hard hit by the financial crisis and the global economic downturn in 2008–2009. Growth in total retail trade virtually stopped in 2013 and even turned down in the first half of 2014. Retail trade has only been supported by the grocery trade, which grew by 2% in 2013, but otherwise retail trade has been weak. The Prisma chain has survived the periods and crises described above without years of losses and the whole chain grew from 16 to 68 units in 30 years.

Chain development and fierce competition forced the Prisma chain management (PCM) to look for new and sustainable operating models for a rapidly growing new chain in the beginning of 90 s. The pilot project was carried out in the Prisma chain in collaboration with an external methodological expert (ME), the author of this paper. It was decided to explore the possibilities of using statistical approaches and mathematical modelling to find new perspectives. One of the Prisma units was selected as the pilot project, which essentially corresponded to the chain management's vision of the basic model of the chain unit.

Four departments from the pilot unit were included in the study: grocery, leisure, clothing and household. All key performance indicators (KPI) for the pilot unit, such as turnover, profit, marketing costs and sales area, were available for the period under review. At the time of the survey (− 92), the Finnish Mark (FIM) was in use in Finland, so all monetary values in the model data presented in Sect. 3 are in FIM. The standard exchange rate used for the changeover from the FIM to the EUR in 2002 was 5.94573.

For modelling purposes, all sales basket data for one week were collected from the pilot unit. The shopping receipt contains the following information: date of purchase, product code and name, price, number of products purchased, method of payment (cash, cheque, credit card, etc.), discount (if any). The total number of shopping receipts per day varied between 2 to 4 thousand. For data analysis, the receipt data were converted into an observation matrix (later basket data), where the entire receipt constitutes a single observation. This phase was highly tedious, since it involved integrating company data bases with the analysis data. The individual purchases on the receipt were combined with product and customer data. As a result of the merging, the sums of price and quantity data and profit margin data were included in the observation. From the product data, information on the nature and characteristics of product groups and categories was also added to the observation. This could be used to understand and exploit the results of the shopping basket analysis.

The generated model can be applied as a general approach. The structure of the model is suitable for any unit or company where there is a need to study the causal structure of purchasing behavior and company KPI data.

The DSS modelling work described in this article is part of an extensive multi-year development process of the Prisma chain, in which the author, as a consultant, was able to contribute to the implementation of the chain's strategy using various statistical and multi-objective modelling methods. The implementation of the strategy required the search for and development of new solution models by combining different software, scientific methods and database data in a new way. These combinations were used to implement and measure the strategy, to guide strategic thinking and to find new tools to achieving competitive advantage.

The challenge for decision support systems is to prove the real help they provide to decision-makers. Generally such systems are described in academic literature soon after their completion, with less attention paid to long-term monitoring. This paper has also sought to look at the long-term impact of the DSS by interviewing the original Chain Manager and Operational Expert to the system and bringing their views on the results achieved into the discussion. The different solution options

generated by the model were found to support the strategy work well and were used as building blocks for exploring and selecting decision options for more than half a decade. The knowledge and experience gained from the model and its development helped to identify new effective ways of working and new business ideas that created competitive advantage and have stood the test of time (Mönkkönen 2021, personal interviews). Prisma's ability to face fierce competition improved and in the coming years the Prisma chain grew from 16 (1992) to 68 units (2020).

The remainder of the study is organized as follows: Sect. 2 describes the S Group, the Prisma chain and its pilot unit. Section 3 describes the research approaches and provides an overview of basket analysis and how cluster analysis can be used to identify customer profiles, and how profit margin analysis and the multi-objective linear programming model (MOLP) can be used to create scenarios to support strategy work. Section 4 will discuss the results of the model with the decision maker and lessons learned from the implementation of the model. Section 5 is reserved for concluding remarks and possible further developments.

## 2 S Group and prisma hypermarket chain

S Group is a large customer-owned Finnish retail and service network with more than 1,800 outlets in Finland (2019). The S Group includes cooperative stores as well as SOK and its subsidiaries operating in the travel and hospitality sector in countries such as Estonia and Russia. Cooperatives are enterprises in which their owners are also their customers.

The S Group operates in supermarkets, hypermarkets, department stores, specialty stores, gas stations, fuel sales and travel and catering trade. The market trade consists of five market chains of different sizes and with different service offerings, of which Prisma is the largest automotive chain (S Group in brief 2021).

The SOK Group's market trading business includes operations in Estonia and Russia. In Estonia, there are six Prisma stores in Tallinn, two units in Tartu and one in Narva (S Group in brief 2021).

In November 2019, the Prisma chain had 68 stores and an online store. Prisma also has stores in Estonia and Russia. The sales area of Prisma stores varies between 4000 and 14,000 $m^2$.

Although each unit in the Prisma chain operates independently, certain activities such as assortment planning, product placement, logistics and strategic decision-making for the whole chain are planned and managed centrally. Product and customer databases are managed both centrally and locally.

In the 1990s, PCM consisted of representatives from the regional administration and Prisma managers. PCM made all major financial decisions and therefore had the final say in the development process. From a DSA perspective, the role of the PCM was to act as the final decision maker (DM). All major projects had to be justified to the DM and their implementation had to be approved separately.

The chain manager (CM) and the chain operations expert (OE), together with an external methodological expert (ME), were responsible for the development and implementation of the whole multiple-criteria decision support system. All major

projects had to be justified to the PCM, which in the 1990s, consisted of the CM and 5 Prisma managers. Implementation of all major projects had to be approved separately.

## 3 Research approaches

### 3.1 Basket analysis and customer profiling

The Pilot unit (PU) included in this study has numerous departments. For closer considerations, four departments have been selected for the DSS study: grocery, leisure, clothing and household. The departments have different numbers of product categories and products depending on store size and assortment class. The pilot unit had 69 product groups and around 35 000 products in the analysis. See Tables 5, 6, 7, 8 in "Appendix" (Fig. 1).

Data aggregation and building of the observation matrix were accomplished putting together shopping basket data with customer and product data. In the observation matrix, products were treated at product group level. For purchasing behavior, it was essential to know which product group was used, not how much. Therefore, binary data were used instead of quantitative data: 1 if a product of a product group was present, 0 if not. When a product was in the customer's shopping basket, it was known where it had been taken from, and by following the product groups it was possible to see which parts of the store customers have visited.

For the final basket analysis, customer profiles (Groups) still need to be produced based on the observation matrix. The profiles were generated using cluster analysis with Wilks' Lambda as the criterion: $\Lambda = |W|/|T|$, where $W$ is the sample pooled within-groups sums of squares and products matrix and $T$ is the sample total sums of squares and products matrix [see, e.g., Mardia et al. (1979), p. 363]. Wilks' lambda is a clustering criterion, which is able to take into account the within-groups correlation structure as well. Because $T$ does not depend on the clusters, we actually minimize $|W|$ [see, for more details (Korhonen 1978)]. When the amount of observations are thousands, it is not possible to find a global minimum within a reasonable time frame. Heuristic algorithms might lead to various local optima. The number of these optima depends on the number of variables. To reduce the number of possible local optima, we used the first seven (7) Principal Component Scores (PCS) instead of

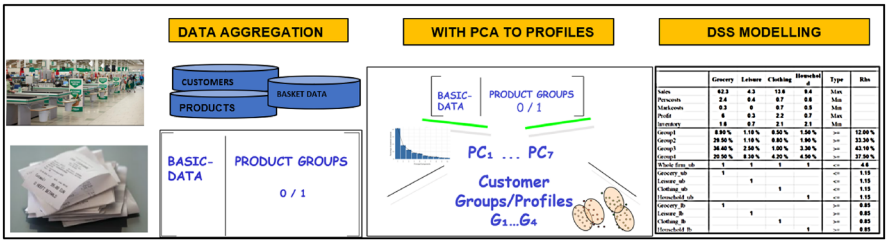


**Fig. 1** From cashiers to DSS-model

**Table 1** Average baskets for each customer group

| Averages in baskets | Group 1 | Group2 | Group3 | Group4 |
|---|---|---|---|---|
| Average cost of the basket | 44.96 | 111.48 | 166.23 | 316.96 |
| Average gross profit | 7.10 | 18.11 | 24.44 | 68.64 |
| Average number of items | 2.8 | 10.3 | 13.4 | 10.2 |
| Percentage of customers | 49 | 31 | 14 | 6 |

**Table 2** The average proportions of the baskets including each product in different product and customer groups

| Group | Grocery (%) | Leisure (%) | Clothing (%) | Household (%) | Percent |
|---|---|---|---|---|---|
| 1 | 8.9 | 1.1 | 0.5 | 1.5 | 49 |
| 2 | 29.5 | 1.1 | 0.8 | 1.9 | 31 |
| 3 | 36.4 | 2.5 | 1.0 | 3.3 | 14 |
| 4 | 20.5 | 8.3 | 4.2 | 4.5 | 6 |
| Total | | | | | 100 |

72 original variables. The first seven principal-components explained about 40% of the total variation. We concluded that 40% was sufficient [see, e.g., Mardia et al. (1979)].

Based on those seven PCS, we performed a cluster analysis. In the preliminary analysis, solutions with 3–7 groups were considered. The four-group solution was chosen as the final solution, because it was the easiest to interpret.

The average amount of the receipt, the average gross profit, the average number of items purchased, and the percentage of the customers in a group are given in Table 1.

To characterize the groups, we studied the product distribution in the basket within each group. The results at the product level are given in "Appendix" in Tables 5, 6, 7 and 8. The results at the product group level are given in Table 2.

The percentages in Table 2 tell how many times each product on average in each product group was included in the basket in a certain group. For example, column 'Grocery' in Group 1, 8.9% in Table 1, tells that each product out of those 21 products in the product group "Grocery" was in 8.9% baskets (Table 5). When the number is small, there are not very many grocery products in the basket.

Based on Tables 1 and 2, customer groups are as follows:

Group 1: Customers with small baskets ("Acute need shoppers")

Basket on average: 2.8 items and total sum 45.0. This group represents 49% of the customers.

Group 2: Basic grocery shoppers ("Daily shoppers")

This group consists of customers who mainly shop in the grocery department. There are 31% of the customers in this group.

Group 3: Large scale grocery shoppers ("Weekly shoppers")

This group is similar to group 2 with the exception that their basket amount is 50% greater. This group represents 14% of the customers. In Table 5 ("Appendix"),

we can see that those customers buy e.g. more meat, meals, canned food, soups, coffee/tea and spices than the customers in group 2.

Group 4: customers with groceries and other items ("Large scale shoppers")

The basket of these customers roughly consists of 50% grocery and 50% other items. The amount of their basket is about three times greater than that of group 2. Six percent of the customers belong to this group.

The big surprise was the large size of group 1. Prisma's strategy is based on the fact that it is a hypermarket, where people most often come by car and do their basic family shopping in one go. The number of visits according to this strategy is lower, but the average purchase is higher. So in the grouping above, group 4 is the group that is in line with the strategy, not group 1.

In a later analysis, we found two things. The clustering was influenced by the fact that the pilot unit is located in the city center, where distances are short and schools and other educational institutions are close by. Young people go shopping every day and may only visit the unit in passing anyway. These factors influence the clustering result. On the other hand, the later analysis revealed that families as a whole used the pilot unit for basic weekly shopping and thus "represented" the clientele of group 4.

As a direct result of the shopping basket analyzes, 49% of customers with small shopping baskets were served by opening express checkouts in Prisma units. Subsequent analysis showed that these customer groups also do most of their shopping in Prismas. These customers came to Prismas to buy only small items because there were no parking problems and the shopping process was easy.

### 3.2 Marginal analysis

> "The strategic goal of the chain management was to create an efficient automotive store that implements new business ideas, where the focus is customer and where ease of purchase, good availability and a high service image as well as a reliable price/quality ratio are achieved." (Mönkkönen 2021).

The OE expressed the wish to create an environment or a set of methods to simulate or play with different options based on existing facts and find reasonable ways to create an efficient automarket required by the strategy. Marginal Analysis compares the additional benefits of an activity with the additional costs of the same activity. It is used as a decision-making tool, for example to estimate the potential profit of a company by comparing the costs and benefits of an activity at the same time.

Our task was to develop a DSA with a model that was easy for management to understand and manage. To achieve this goal, we proposed a multi-objective linear programming MOLP model for marginal analysis. Here, by the term marginal analysis, we refer to an analysis that allows management to consider several different reasonable directions for improvement.

In marginal analysis, the user may have several objectives such as total profit, total sales, etc. We assume that (s)he is able to evaluate possible non-dominated directions of improvement by using several objectives, simultaneously. The term non-dominated direction refers to a direction for which there exists no other direction,

which is as good as the direction under investigation on all objectives and is better for at least one objective.

### 3.2.1 The proposed model

Suppose there are $m$ objectives and $n$ departments, which contribute to each objective. Let $a_{ij}$ denote the contribution of department $j$ to objective $i$. The current value of objective $i$, $i \in M = \{1, 2, \ldots, m\}$, is obtained by summing $a_{ij}$ over $n$ departments:

$$y_i = \sum_{j=1}^{n} a_{ij}, \quad i \in M. \tag{1}$$

We assume that if we change the "size" of department $j$ by $\Delta x_j$, then its contribution to each objective is linear, i.e.,

$$\Delta y_{ij} = a_{ij} \Delta x_j, \quad i \in M \text{ and } j \in N = \{1, 2, \ldots, n\}. \tag{2}$$

The assumption is reasonable, when we study incremental changes. Equation (2) enables the management to evaluate the effects of marginal changes: $a_{ij} \rightarrow a_{ij}x_j = a_{ij}(1 + \Delta x_j)$, $i = 1, 2, \ldots, m$, $j \in N$, in the current contributions to objectives $y_i$, $i = 1, 2, \ldots, m$, of the PU. We assume that the change in "size" may mean change in resources (money, space, personnel, etc.), in quality of service, in development strategies, etc. To make the exposition more clear and concrete, we will use the term "resource" instead of "size".

Furthermore, we take into account the needs of each of $k$ customer groups considering the total needs of the customer.

$$v_i = \sum_{j=1}^{n} g_{ij}, \; i \in K = \{1, 2, \ldots, k\}, \tag{3}$$

where $g_{ij}$, $i = 1, 2, \ldots, k$ and $j = 1, 2, \ldots, n$, is "demand intensity/need" of product group (department) $j$ of customer group $i$, and $v_i$ is the aggregate demand intensity/need over product groups. As the proxy measure for these intensities are used proportions in Table 2. As we can see from Table 2, all $v_i = 100$, initially. As before, we assume that the marginal changes in resources change the value coefficients linearly: $g_{ij} \rightarrow g_{ij}(1 + \Delta x_j)$, $i = 1, 2, \ldots, k$.

Without loss of generality, let us assume that the management wants to maximize all the objectives. Then the multiple objective linear programming model is as follows:

$$
\begin{aligned}
&\max \quad y_i = \sum_{j=1}^{n} a_{ij}x_j, i \in M \\
&\max \quad v_i = \sum_{j=1}^{n} g_{ij}x_j, i \in K \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_j \le np \\
&x_j \le q, j \in N \\
&x_j \ge r, j \in N, q \ge r \ge 0,
\end{aligned} \tag{4}
$$

where $p > 0$ denotes the maximal allowable fractional change in the total business, $q$ is the upper bound and $r$ is the lower bound for change of each department.

The first group of objectives $y_i$, $i = 1, 2, \ldots, m$, represents the objectives of the hypermarket, and the second group of the objectives $v_i$, $i = 1, 2, \ldots, k$, represents the demand intensity of customer groups. If $p > 1$, then we assume that the management can evaluate how additional resources affect the objective functions. The maximal change in each department is given by $q$. Usually, $q \ge 1$, but if $q < 1$, then the resources are reduced from all departments. Number $r$ specifies the maximal reduction in the resources of a department.

The management can evaluate reasonable directions of improvement by using all objectives simultaneously, or it can deal with some objectives as constraints. In the following considerations, we assume that the management only wants to make changes which keep the customer needs at the current level. The model used in the sequel is as follows:

$$
\begin{aligned}
&\max \quad y_i = \sum_{j=1}^{n} a_{ij}x_j, \quad i \in M \\
&\text{subject to} \\
&\sum_{j=1}^{n} g_{ij}x_j \ge h_i, \quad i \in K \\
&\sum_{j=1}^{n} x_i \le np \\
&x_i \le q, \quad j \in N \\
&x_j \ge r, \quad j \in N.
\end{aligned} \tag{5}
$$

This is a multiple objective linear programming MOLP model and may be solved using whatever LP-software is available. The problem requires a specific algorithm, because no unique optimal solution exists for an MOLP model [see, e.g., Steuer (1986)]. The objective of the decision-maker is to choose a compromise solution

from among the set of non-dominated solutions. The set of all non-dominated solutions is called the efficient frontier.

To solve the problem, we used the VIG software package developed by Korhonen (1987), because it is easy to use and does not require any previous knowledge of computers or multiple objective linear programming models. Pareto Race plays a central role in the VIG system. Its user interface is based on visual interaction. It offers the user the possibility to evaluate non-dominated solutions dynamically. The user may search the set of non-dominated solutions by stating, in a flexible manner, which goal or goals (s)he would like to improve [see, for more details Korhonen and Wallenius (1988)].

### 3.3 Implementation

The DM has five conflicting objectives, among which (s)he must find the best balance. The objectives to be maximized are: sales (Sales) and profit (Profit), the objectives to be minimized are personnel costs (Perscost), marketing costs (Markcost) and the value of inventories. The coefficients of the objective functions are generated from the information in the pilot unit's Profit and Loss Account. The coefficients for the customer profiles have been generated from the basket analysis and cluster analysis described in Sect. 3.1.

In the following, we will demonstrate the use of the model in a practical case. We assume that the DM has expanded the sales space of the hypermarket by 15%, and (s)he would like to plan its use such that the solution increases the values of his/her "important objectives".

Furthermore, the DM has decided to re-organize the whole sales space within the allowable range. In Model $p=q=1.15$. (S)he may restrict the maximum reduction of one department to at most 15%. Thus $r=0.85$. The final coefficients of the model are given in Table 3.

We may simply modify the original model in such a way that the DM is able to consider the relative changes in the objectives instead of absolute.

Potential solutions/scenarios are reviewed in Table 4. The first four rows refer to the four departments and the last five rows to the five objectives used in the evaluation. The current situation is shown in column current, where $x_j=1$, initially, $j=1$, 2, 3, 4. The corresponding current values of the objectives are 100. When the value of a decision variable is greater than 1, let us say 1.10, it means that the model proposes a 10% growth for that department. The basic values for the objectives are the same, but the interpretation is different.

Solution 1: Maximizing profit without increasing personnel and marketing costs

The solution is shown in solutions/scenarios column 1 of Table 4. The profit increases by 1.56% and sales by 0.75%. The inventory is reduced by 2.6%. To achieve this, the resources of the household department have to be reduced by 15% while the grocery and the clothing departments have to be increased by 2 and 5%.

Note that the numbers are not essential information, but the direction they indicate. Based on this solution, the recommendation to the DM would be to try to find

**Table 3** Structure of the model

| | Grocery | Leisure | Clothing | Household | Type | Rhs |
|---|---|---|---|---|---|---|
| Sales | 62.3 | 4.3 | 13.6 | 9.4 | Max | |
| Perscosts | 2.4 | 0.4 | 0.7 | 0.6 | Min | |
| Markcosts | 0.3 | 0.1 | 0.7 | 0.5 | Min | |
| Profit | 6.0 | 0.3 | 2.2 | 0.7 | Max | |
| Inventory | 1.6 | 0.7 | 2.1 | 2.1 | Min | |
| Group 1 | 8.9% | 1.1% | 0.5% | 1.5% | ≥ | 12.0% |
| Group 2 | 29.5% | 1.1% | 0.8% | 1.9% | ≥ | 33.3% |
| Group 3 | 36.4% | 2.5% | 1.0% | 3.3% | ≥ | 43.1% |
| Group 4 | 20.5% | 8.3% | 4.2% | 4.5% | ≥ | 37.5% |
| Whole firm_ub | 1 | 1 | 1 | 1 | ≤ | 4.6 |
| Grocery_ub | 1 | | | | ≤ | 1.15 |
| Leisure_ub | | 1 | | | ≤ | 1.15 |
| Clothing_ub | | | 1 | | ≤ | 1.15 |
| Household_ub | | | | 1 | ≤ | 1.15 |
| Grocery_lb | 1 | | | | ≥ | 0.85 |
| Leisure_lb | | 1 | | | ≥ | 0.85 |
| Clothing_lb | | | 1 | | ≥ | 0.85 |
| Household_lb | | | | 1 | ≥ | 0.85 |

*ub* upper bound, *lb* lower bound

**Table 4** Set of potential solutions/scenarios for the problem in Table 3

| | Current | Solutions/scenarios | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| *Decision variables* | | | | | | |
| Grocery | 1.00 | 1.02 | 1.15 | 1.15 | 1.14 | 1.12 |
| Leisure | 1.00 | 1.00 | 0.85 | 1.00 | 1.01 | 0.85 |
| Clothing | 1.00 | 1.05 | 1.09 | 1.09 | 1.36 | 1.15 |
| Household | 1.00 | 0.85 | 0.85 | 0.85 | 0.00 | 0.85 |
| *Objectives* | | | | | | |
| Sales | 100.00 | 100.75 | 109.44 | 115.55 | 104.99 | 108.57 |
| PersCosts | 100.00 | 100.00 | 106.59 | 115.57 | 100.00 | 106.13 |
| MarkCosts | 100.00 | 97.94 | 102.00 | 119.14 | 86.30 | 104.47 |
| Profit | 100.00 | 101.56 | 110.20 | 114.60 | 110.37 | 110.01 |
| Inventory | 100.00 | 97.44 | 100.00 | 118.23 | 82.94 | 101.43 |

out ways to make the customers to spend more money for grocery products and clothing.

Solution 2: Inventory level is kept at the current level

This solution is given in solutions/scenarios column 2 of Table 4. Profit increases by 10.2% and sales by 9.4%. Personnel costs are increased by 6.6% and marketing costs are increased by 2%. To achieve this, the resources of the leisure and household departments have to be reduced by 15% while grocery and clothing departments have to be increased by 15 and 9%.

The strategy is mainly the same as in solution 1. The only significant difference is that there is no sense to try to keep the leisure department at the current level.

Solution 3: Increasing the leisure and the household departments; keeping the grocery and clothing departments at the level of Solution 3

The solution that meets these conditions is shown in solutions/scenarios column 3 of Table 4. The resources of the leisure department are increased up to the original level, but household is reduced by 15%. In this solution, the sales, personnel cost, marketing cost, profit and inventory are increased by 15.6, 15.6, 19.1, 14.6, 18.2%, respectively.

This solution tells that increasing the leisure department has some effects on sales and profit, but primarily it increases the costs. The main problem of this solution is that the costs are increasing more rapidly than profit.

Solution 4: Maximizing profits without upper and lower bound restrictions

This solution increases profit by 10.4% (solutions/scenarios column 4). The resources of the grocery, the leisure and the clothing departments are increased by 14, 1 and 36%, respectively; and the resources of the household department are reduced down to zero.

This solution tells that household is a department which is not very successful on any objective. Increasing grocery and clothing departments improves sales and profit and keeps the costs at a low level. But this solution conflicts with the original business idea of providing a wide assortment.

Solution 5: Proposed possible final solution

This solution is shown in solutions/scenarios column 5 of Table 4. The resources of the grocery and the clothing departments are increased by 12 and 15%, respectively, whereas those of the leisure and the household departments are both reduced by 15%, respectively. Furthermore, sales, personnel costs, marketing costs, profit and inventory go up by 8.6, 6.1, 4.5, 10.0, and 1.4%, respectively. The increase in profit is, however, more rapid than the growth of the expenses.

Increasing grocery and clothing departments improves sales and profit. However, the costs are increased as well.

The working team responsible for the design and operation of the DSS model presented the structure and results of the support system to the DM and the entire team and the DM felt comfortable with solution 5, which was implemented. In our case the term “implementation” meant that the measures shown by solution 5 were systematically put to force.

## 4 Decision support system and user experiences

The DSS model was created together with the OE and the author (the external methodological expert). We used the VIG software package developed by Korhonen (1987) to solve the problem because it was easy to use and required no prior knowledge of computers or multi-objective linear programming models. Pareto Race plays a central role in the VIG system developed by Korhonen and Wallenius (1988). The VIG software represented state-of-the-art software at the time. The software made Marginal Analysis possible. At the time we were not aware of other software systems which could have been used for this purpose. The OE easily learned how to use and work with the model. The results were immediately visible and could be used to examine alternatives and assess their appropriateness.

The operational team learned how to process the data themselves using MS Excel and the available modelling tools (VIG). The team also prepared presentation material for the decision-making bodies (Fig. 2).

In the example above, three objectives are considered at the same time. The objectives and their values can be varied and thus solutions can be viewed from different perspectives. During the Pareto Race process, the user's eyes were "opened" to the reality embodied in the model. First there is admiration, then confusion and finally a realization: "Can this be real?". The interdependencies of the model told the user the effectiveness of the actions in a "what-to-do-to-achieve" or "what-if" analysis and broadened the view for a strategy-type discussion (Huju 2021).

The collaboration of the DSS design team highlighted that understanding, using and benefiting from a decision support system are different things. A model can be understood and accepted without knowing how to use it or even wanting to use it.

The implementation of a DSS model usually causes problems if the following points are not given sufficient attention. The DSS must be

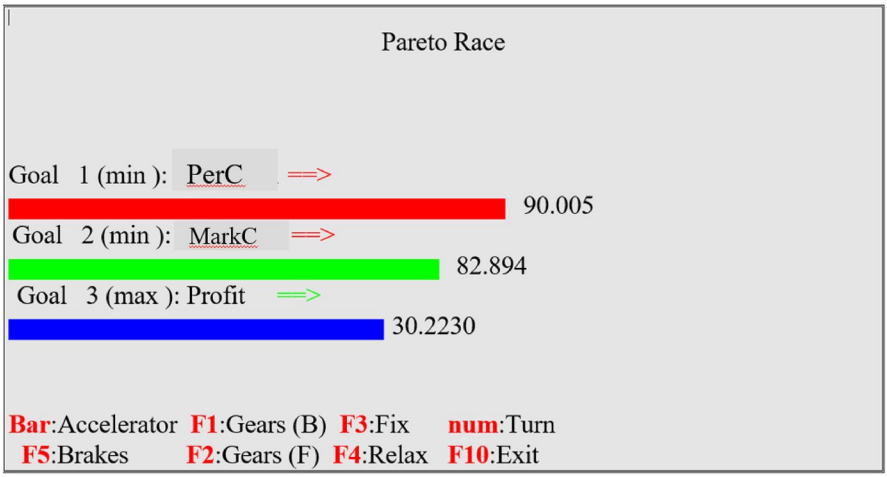


**Fig. 2** Pareto race in marginal analysis

- implemented in a way that is tailored to each level of the organization,
- clearly presented and documented for each user separately,
- firmly embedded in the organization's strategic plans and roadmap, and
- teachable to users in such a way that the knowledge remains within the organization.

The design team for the DSS model was also a user group, so the implementation of the model was not problematic.

It was decided to present five different scenarios to the chain's management. They considered the scenarios generated by the model to be a good support for their strategy work and used them as building blocks for exploring and selecting decision making directions. The knowledge and experience gained from the model and its development helped to identify new ways of working and provided effective ways to search for and find new business ideas.

Prisma's ability to face fierce competition improved, and over the coming years the chain grew from 23 to 68 units (2020). The chain manager and OE involved in the development of the chain have seen and experienced the results of this work by following the success story of the Prisma chain. All the knowledge and skills that were gathered for the modelling process and the support systems served as a solid basis for the strategic planning work and as one of the most important elements of the Prisma success story (Mönkkönen (Mönkkönen 2021)).

## 5 Concluding remarks

This paper describes the decision support methodology used in the development process of the S Group's Prisma hypermarket chain. Management was looking for a new and sustainable operating model for a rapidly growing chain. Fierce competition forced the company to search for new business ideas, tools and methods that would provide a clear competitive advantage.

To find new perspectives, we used statistical approaches and various decision support system options, such as multi-criteria modelling. A database was available for research and analysis, including data on purchasing behavior and key performance indicators.

The approach took into account the role and impact of customers. Customer behavior was included in the analysis through shopping basket data. From these, an observation matrix was created combining shopping basket data, product data and customer background information. Using multivariate methods, customer groupings and profiles were created with the data from the observation matrix. Using the customer profile and KPI data, a multi-criteria decision support system (MCDSS) was produced to support strategic planning.

The structure of the model was designed according to the given assumptions and constraints. The aim of the model was to combine key performance indicators (KPI) and customer data in the chain in a way that balances the role and importance of both in an understandable and meaningful way.

> This model and approach took us one level higher in our thinking. We saw concretely how customer profile structures shape the outcome of operations. On the other hand, the model also highlighted the constraints to work with—it makes no sense to reach for the moon if resources won't allow it. And also that we can, in the spirit of what to do—to achieve, take decisions to achieve our goals. (Huju 2021)

The design team reported five different solutions to illustrate possible scenarios as a basis for strategic planning. These were presented to decision-makers. The DM was able to examine efficient options without any "infeasible" solutions among them. One of the solutions was found to be good and was selected as the final deliverable to be reported.

The DSS model allowed the DM to understand the dependencies and independencies in the Hypermarket's operations. The Scenarios generated by the model served as a good basis for strategy work and for building material for future work. It could be used as a starting point to search for new directions for decisions.

> The solutions presented in the modelling tool showed how the hypermarket structure works under the given conditions. In strategy work, we often play with assumptions and the power of experience. The reported scenarios helped our strategy work by leaps and bounds and opened our eyes to the consequences and implications of the options. (Mönkkönen 2021)

Further development work is left to extend the DSA through the use of customer listening. Customer listening provides a great deal of additional information on customer attitudes, behaviors and ways of acting.

## Appendix

As noted in Sect. 2, the sales receipt of each customer contains information about the total purchase in FIM, profit, number of items purchased, and 69 binary variables for the product groups. The results of the principal-component analysis and cluster analysis are given in Tables 5, 6, 7 and 8—one for each department. Theses tables also list the sixty-nine product groups. Entry in a table represents the fraction of individuals in a group who bought a given item group.

For example, row 1 of Table 5, represents the fraction in each group who bought meat, i.e., 0.042 (or 4.2%) in group 1, 0.220 (or 22.0%) in group 2, 0.359 (0r 35.9%) in group 3, and 0.183 (or 18.3%) in group 4 bought meat. The last row of each table gives the average for each group.

The coefficients of the variables in the constraints set 2 in table (one constraint for each group) represent the percent of a group that bought items in a given department. For the convenience we list the coefficients of the variables here:

| | Grocery | Leisure | Clothing | Household |
|---|---|---|---|---|
| Group 1 | 74.424 | 8.852 | 4.380 | 12.345 |

**Table 5** Grocery department

| Grocery | Customer groups | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Meat | 0.042 | 0.220 | 0.359 | 0.183 |
| Sausage | 0.084 | 0.634 | 0.559 | 0.355 |
| Milk | 0.260 | 0.905 | 0.829 | 0.484 |
| Fish | 0.279 | 0.335 | 0.396 | 0.226 |
| Fruits | 0.107 | 0.584 | 0.492 | 0.323 |
| Vegetables | 0.037 | 0.406 | 0.336 | 0.204 |
| Bread | 0.114 | 0.687 | 0.526 | 0.333 |
| Meal | 0.101 | 0.327 | 0.481 | 0.258 |
| Juices | 0.032 | 0.161 | 0.254 | 0.097 |
| Canned food | 0.025 | 0.092 | 0.327 | 0.113 |
| Frozen dinners | 0.040 | 0.210 | 0.111 | 0.086 |
| Soups | 0.019 | 0.044 | 0.336 | 0.038 |
| Sugar | 0.010 | 0.003 | 0.238 | 0.043 |
| Toys | 0.172 | 0.251 | 0.274 | 0.253 |
| Coffee/tea | 0.168 | 0.128 | 0.668 | 0.253 |
| Spices | 0.025 | 0.055 | 0.388 | 0.086 |
| Drinks | 0.073 | 0.319 | 0.169 | 0.199 |
| Cigarettes | 0.054 | 0.171 | 0.111 | 0.102 |
| Plastic bags | 0.123 | 0.493 | 0.439 | 0.253 |
| Feminine needs | 0.073 | 0.123 | 0.261 | 0.226 |
| Toiletries | 0.040 | 0.056 | 0.082 | 0.183 |
| Averages | 0.089 | 0.295 | 0.364 | 0.205 |

**Table 6** Clothing department

| Clothing | Customer groups | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Men's cloths | 0.030 | 0.020 | 0.040 | 0.231 |
| Garments | 0.000 | 0.000 | 0.000 | 0.038 |
| Clothes | 0.044 | 0.056 | 0.174 | 0.290 |
| Women's cloths | 0.000 | 0.000 | 0.000 | 0.129 |
| Girls underwear | 0.021 | 0.036 | 0.027 | 0.097 |
| Girls cloths | 0.002 | 0.000 | 0.004 | 0.011 |
| Children's cloths | 0.013 | 0.004 | 0.018 | 0.043 |
| Men shoes | 0.000 | 0.000 | 0.000 | 0.005 |
| Women shoes | 0.000 | 0.000 | 0.000 | 0.054 |
| Children shoes | 0.000 | 0.001 | 0.000 | 0.000 |
| Leather goods | 0.007 | 0.001 | 0.011 | 0.016 |
| Averages | 0.011 | 0.011 | 0.025 | 0.083 |

**Table 7** Leisure-time departmen

| Leisure | Customer groups | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Toys | 0.021 | 0.021 | 0.027 | 0.016 |
| Printed matter | 0.074 | 0.144 | 0.154 | 0.183 |
| Paper | 0.000 | 0.000 | 0.009 | 0.000 |
| Hi-fi | 0.023 | 0.014 | 0.056 | 0.038 |
| Guns | 0.000 | 0.000 | 0.022 | 0.005 |
| Hiking | 0.050 | 0.054 | 0.158 | 0.237 |
| Cameras | 0.015 | 0.002 | 0.007 | 0.022 |
| Other furniture | 0.007 | 0.014 | 0.020 | 0.043 |
| Flowers | 0.019 | 0.022 | 0.018 | 0.059 |
| Electrical appliances | 0.036 | 0.052 | 0.073 | 0.129 |
| Cookware | 0.001 | 0.000 | 0.000 | 0.000 |
| Locks | 0.002 | 0.004 | 0.007 | 0.011 |
| Paints | 0.000 | 0.000 | 0.002 | 0.000 |
| Saws | 0.011 | 0.012 | 0.009 | 0.022 |
| Wood | 0.002 | 0.001 | 0.007 | 0.016 |
| Tools | 0.001 | 0.004 | 0.007 | 0.022 |
| Car accessories | 0.003 | 0.003 | 0.007 | 0.011 |
| Gasoline | 0.002 | 0.000 | 0.009 | 0.000 |
| Averages | 0.015 | 0.019 | 0.033 | 0.045 |

**Table 8** Household department

| Household | Customer groups | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Other shoes | 0.000 | 0.000 | 0.000 | 0.102 |
| Material stuff | 0.000 | 0.000 | 0.000 | 0.086 |
| Sheet | 0.006 | 0.011 | 0.020 | 0.048 |
| Thread | 0.004 | 0.015 | 0.011 | 0.038 |
| Furniture | 0.003 | 0.003 | 0.004 | 0.022 |
| Kitchen equipment | 0.016 | 0.027 | 0.033 | 0.118 |
| Vessel | 0.013 | 0.014 | 0.011 | 0.151 |
| Machines | 0.005 | 0.007 | 0.000 | 0.027 |
| Slabs | 0.000 | 0.000 | 0.000 | 0.000 |
| Plastics | 0.000 | 0.000 | 0.000 | 0.000 |
| Sanitary | 0.000 | 0.000 | 0.000 | 0.000 |
| Electrical appliances | 0.036 | 0.052 | 0.073 | 0.129 |
| Cookware | 0.001 | 0.000 | 0.000 | 0.000 |
| Locks | 0.002 | 0.004 | 0.007 | 0.011 |
| Nails | 0.000 | 0.000 | 0.000 | 0.000 |
| Paints | 0.000 | 0.000 | 0.002 | 0.000 |
| Saws | 0.011 | 0.012 | 0.009 | 0.022 |
| Wood | 0.002 | 0.001 | 0.007 | 0.016 |
| Tools | 0.001 | 0.004 | 0.007 | 0.022 |
| Averages | 0.005 | 0.008 | 0.010 | 0.042 |

| | Grocery | Leisure | Clothing | Household |
|---|---|---|---|---|
| Group 2 | 88.630 | 3.218 | 2.368 | 5.783 |
| Group 3 | 84.347 | 5.778 | 2.246 | 7.629 |
| Group 4 | 54.627 | 22.177 | 11.126 | 12.070 |

These are computed from the last rows in Tables 5, 6 and 7. For example, the coefficient for group 1 for the grocery department is equal to

$$74.424 = 0.089/(0.089 + 0.011 + 0.005 + 0.015)$$

or 74.4%, or 74.4% of the customers in group 1 have grocery items in their basket.

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