# A METHODOLOGY FOR MARKETING STRATEGY OPTIMIZATION

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## RESUMO

Este trabalho descreve uma metodologia para suportar decisões relacionadas à estratégia de marketing de uma empresa. Informações de como os diferentes segmentos de clientes avaliam o produto ou serviço, bem como o impacto no processo decisório são analisados e utilizados de uma maneira sistemática. Os posicionamentos dos competidores no mercado são levados em consideração para simular o comportamento dos clientes, utilizando o processo de decisão multicritério AHP (processo hierárquico analítico), em uma simulação baseada em eventos. Os cálculos geram uma elasticidade pontual da captura de mercado, em função dos valores percebidos pelos clientes. Esses resultados são utilizados como entrada para um modelo de otimização para estimar a melhor estratégia de marketing da empresa no cenário simulado.

**PALAVRAS CHAVE: Estratégia de Marketing, AHP, Otimização.**

**Área Principal: (1) AD&GP – PO na Administração e Gestão da Produção ou (2) ADM – Apoio à Decisão Multicritério**

## ABSTRACT

This paper describes a methodology to support the decision making process related to the marketing strategies of a company. Information about how customers segments value a product or the provided services, as well as the potential impacts of the decision process are assessed and used in a systematic way. The competitors' positioning in the market are taken into account to simulate the sector's behavior using the multicriteria decision process AHP (Analytic Hierarchy Process) in an event based context. The simulations provide results in terms of the point elasticity of the market share according to the customers' perceived values. These results are used as inputs to an optimization model to estimate the best marketing strategy, for the given scenario.

**KEYWORDS: Marketing Strategy, AHP, Optimization.**

**Main area: (1) AD&GP – PO na Administração e Gestão da Produção ou (2) ADM – Apoio à Decisão Multicritério**

## 1. Introduction

Choosing the best marketing strategy is a vital task of any company, but it may involve great uncertainty and risks. Any action impacting the marketing 4P's (Product, Place, Price and Promotion) may influence directly both the market share and the product costs and, thus, the profitability of a company. On the other hand, huge marketing efforts can drain a significant amount of investments, without a satisfactory expected return. In fact, for over 50 years research on the market response has drawn considerable attention and many models has been proposed to explain how marketing mix variables influence the sales (Hanssens, Parsons and Schultz, 2001).

Throughout this paper, a decision support model applicable to the selection of the market strategies will be described, comprising the following macro-steps:

- Market Assessment: Obtain reliable data about the market, in terms of the augmented product features that influence customers' decision and how each competitor aims at fulfilling these needs;
- Market Share Estimative: Given the information of step 1, a model is constructed to estimate the variations of market share based on the product features;
- Market Strategy Recommendation: Having characterized how the product features may impact the market share and the sales, an optimization algorithm is used to select a set of marketing actions, considering as the performance index, the gross profit.

The statistics based decision model proposed in this work may be used as a complement to more traditional techniques.

### 1.1 Market Share Estimative

The dynamic behaviors of the modern industries are becoming faster and the competition tougher, so that having the capability to estimate the market share beforehand is a huge competitive advantage, as it can be used to provide means to intervene pro-actively, reducing the potential threats and taking advantage of market opportunities.

Also, market share is often used as a key performance indicators of high managers, indicating whether sales performance are satisfactory or not and whether corrective actions should be taken.

A variety of analytical models to describe the market share are available, ranging from simple one equation models to more sophisticated ones (Cooper, 1988). In particular, Kotler (1984) proposed the *fundamental theorem* of market share, described by the following equation:

$$s_i = \frac{M_i}{\sum_{j=1}^{m} M_j} \quad \text{(i)}$$

in which $m$ is the number of total players in market, $M_i$ is the marketing effort of player $i$ and $s_i$ is the market share of player $i$. According to this equation, a company's market share would be proportional to its marketing effort. This is a very general equation and is used as the base for many other models. For example, multiplying each $M_i$ and $M_j$ by a coefficient representing the effectiveness of each marketing campaign (Cooper, 1988) would lead to a different model, in which different firms with same marketing expenses would have different market shares, depending on how effective they are in terms of their marketing actions. The goal of the model proposed in this work, as it is explained in next section, is to estimate the share of sales of each competitor, assuming that they are proportional to a measure of how well they fulfill the customers needs and values.

Even with a large number of available techniques, the choice of the most suitable one will depend on many aspects:

- Industry dynamics;
- Company's knowledge about customer's values and decision process;
- Company's knowledge about competitors product and strategies;
- Entry barriers for new competitors;
- Product substitutes;
- Others aspects of Porter's 5 forces (Porter, 2008).

The model proposed in this work is applicable to companies with a good knowledge about customers' values and competitors' product features.

## 2. Methodology Description

The Figure 1 summarizes the methodology proposed in this work.

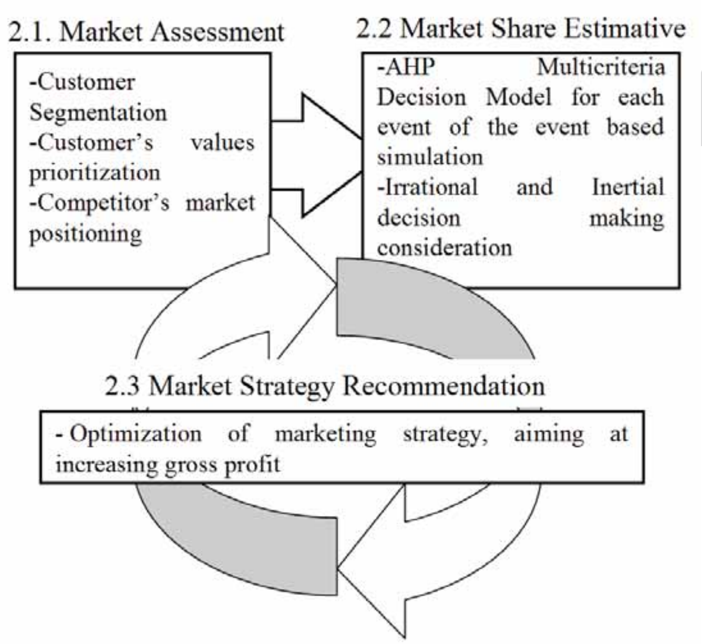



Figure 1: Summary of Proposed Methodology

In order to provide means for a systematic evaluation of the proposed methodology, synthetic data were used. Therefore, the original and the uncertainty corrupted data are both available and comparisons with results associated to the "ground truth" is made possible.

### 2.1 Market Assessment

The first step of the proposed methodology is to estimate some customers and competitors characteristics. In summary, it is necessary to know what product features drive customer's decisions (hereafter referred as customers' values) and how each competitor satisfies each one of these values.

### 2.1.1 Customer's values by segment – Conjoint Analysis

In most industrial sectors, it is virtually impossible to have information about the decision process of all individual customers. This is the reason why the first step is to segment the customers into some classes, according to their values: by grouping them into a small number of clusters with approximately homogeneous values, it is possible to reduce the problem into a manageable size. The simulations are, therefore, based on segmented population average, together with the expected variability, as described bellow:

1. Identify key criteria for customer decision making. In this example, as illustrated in Figure 2, the first hierarchical level is derived from the marketing 4P's, described in Kotler (2008). Sublevels can be added, to further refine customer decision model:

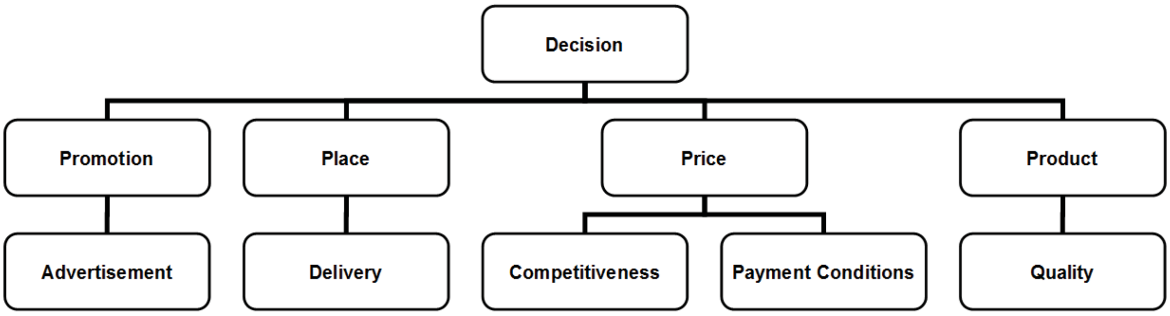



Figure 2: Decision Criteria Modeling

2. A number of customers are interviewed concerning their values, using the pairwise comparison matrix proposed by Saaty (2008). At the end, the goal is to derive the priority matrix for each customer. This work will not focus on how to obtain the values perceived by the customer. Techniques of conjoint analysis can be found in Wind and Green (2005).
3. The priority matrix, together with other customer's characteristics (age, gender, geographical location and others), are used to finally cluster the customers into different segments. A large volume of literature is available concerning how to cluster customers, resulting in what is generally known as "Personas", as described in Satish and Gary (2012). Many of these references propose the application of some non-supervised machine learning techniques (such as the hierarchical or k-means clustering) to identify the segments.
4. For each Persona, the average priority vector, as well as an estimative of its variability, is defined. In the example described in this paper, each value of this vector is considered as a random variable drawn from a gaussian process with known mean and standard deviation.

In the Figure 3, the greater the number associated with a product characteristics and a Persona, the more important is that feature for customer acquisition decision making:

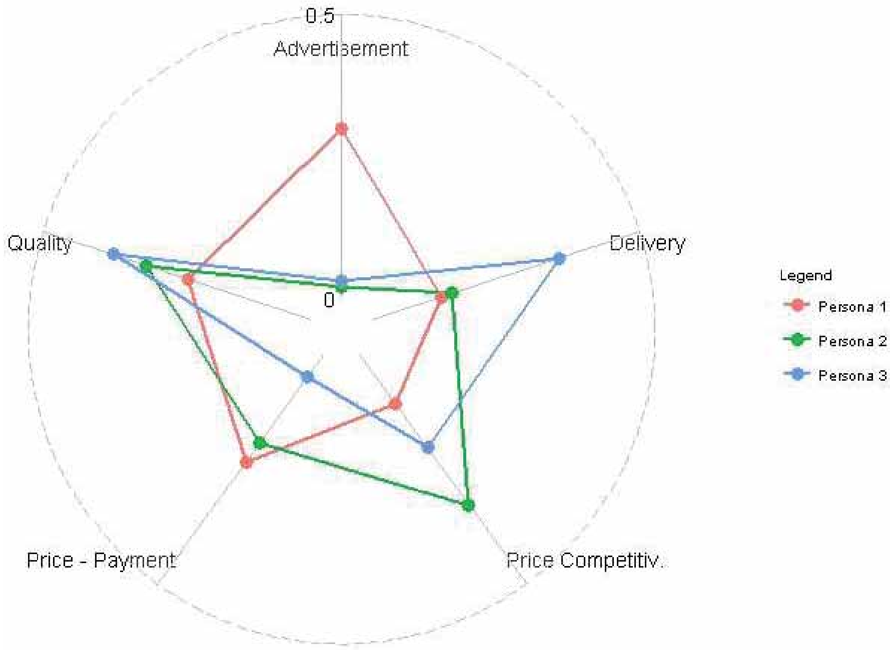



Figure 3: Customers Values, per Persona

### 2.1.2 Competitor's marketing positioning

With the customer's values in hands, it is important to know how each competitor fulfills these values. In cases in which the direct interview of the main competitors is difficult to carry out, this task can be based on the customers opinion or by consulting specialist in the field. In Figure 4, the competitors' positioning were ranked with real numbers, ranging from 0 to 10:

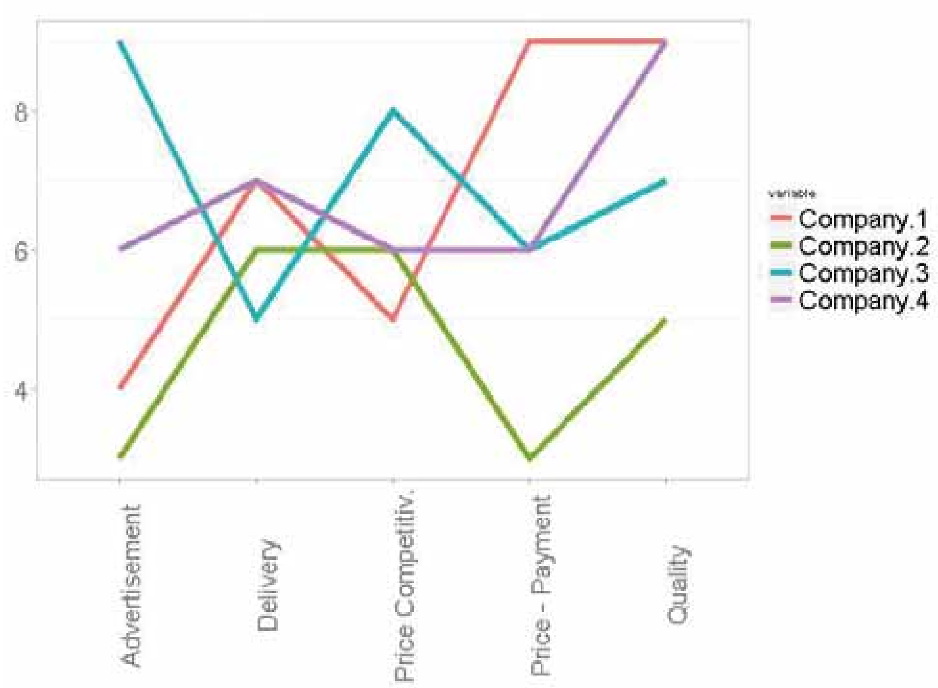



Figure 4: Competitors Positioning

In this example, Company 1 has the best Advertisement and Price offers, while the delivery is considered the worst among competitors and payment condition and produt quality are best than competitor 2. This competitor's marketing positioning is similar to the competition analysis described in the Blue Ocean methodology, by Kim and Mauborgne (2005).

Customer and competitor's data are the foundation of this methodology. Even though they may be difficult to acquire with a high confidence level in a first moment, the expectation is to refine these values as more market information are collected.

### 2.2 Market Share Estimative

With the competitors' and customers' information in hands, the next step is to estimate the market share. This step can be modeled by an event based decision process for each customer segment, using the AHP (Saaty, 2008). Note that here, the AHP is being used not to support any decision, but rather to estimate what would be the rationale of each customer segment. Also, this multicriteria decision making metodology was used due to its wide popularity, ability to handle hierarquical values and agreggate different specialists opinions. However, other multicriteria decision making methodologies could be used in this step to represent each customer segment rationale.

In order to carry out the market share simulation, other parameters need also to be estimated:

- Current Market Share per Persona (obtained after the customer segmentation in subsection 2.1.1);
- Inertia parameter (per Persona): between 0 and 1, represents the probability that customer will not make a new decision process and, thus, will keep the current supplier;
- Irrationality parameter (per Persona): between 0 and 1, represents the probability of a random decision by the customer.

The process to estimate the market share is summarized in the following pseudo-code:

```
for i = 1: N_iterations
    Persona [i] = draw_which_Persona
    DecisionType[i] = draw_decision_behavior      // based on Persona
        if        DecisionType[i] == Inertia:
                  decision[i] = draw_from_current_market_share

        else if   DecisionType[i] == Irrational:
                  decision[i] = random

        else:
                  decision[i] = AHP_synthesis(mean, std)
```

The "*mean*" and "*std*" input of the last line of the pseudo-code indicates that we can have slightly different decisions, even inside the same Persona group, because the priority vector is assumed to be random, drawn from a gaussian probability density function with known mean and standard deviation, as described in section 2.1.1.

The vector *decision* will have all decisions of the *N_iterations* event based simulation. By summing up the total decisions for each one of the 4 competitors and dividing by N_iterations, it is possible to obtain the estimated market share.

### 2.3 Choosing the best marketing actions

At this point, a model is available to express the partial derivative of the market share with respect to the market positioning of each competitor (described in section 2.1.2) and, thus, it is possible to compute the point elasticity by the following formula (Cooper and Nakanishi, 2008):

$$e_{si} = \frac{\partial s_i}{\partial X_{ki}} \cdot \frac{X_{ki}}{s_i} \qquad \text{(ii)}$$

in which $s_i$ is the market share for Persona i and $X_{ki}$ is the perceived $k$ value of Persona $i$. This parameter allows us to determine what is the effect of market share, given any modification in the product value of a company, as perceived by the customer.

The possible marketing actions can now be classified in terms of how they affect the marketing positioning (as described in section 2.1.2, Figure 4). For example, table 1 shows some marketing actions:

Table 1: Examples of marketing actions

| | Impact on... | | | | | |
|---|---|---|---|---|---|---|
| Action | Advert. | Delivery | Price Compet. | Price - Payment Cond. | Product Quality | Cost of action |
| a. Invest on specialized media 1 | 0.05 | | | | | $ 1.5k |
| b. Invest on specialized media 2 | 0.1 | | | | | $ 10k |
| c. Invest on specialized media 3 | 0.2 | | | | | $ 100k |
| d. Change product quality | | | -0.2 | | 0.4 | $ 40k |
| e. Increase Payment Flexibility | | | -0.2 | 0.4 | | $ 0 |
| f. Agreement with logistics provider | | 1.0 | -0.2 | | | $ 5k |
| g. Acquisition of a new distribution center | | 1.5 | | | | $ 1.5M |
| h. Reduce/ Increase Price | | | 0.2 | | | $ 0 |

According to the table, investing in a specialized media would cost $10k, but would increase the Advertisement value by 0.1. Also, increasing the product quality by 0.4 units would cost $40k (fixed) plus a variable cost which would impact competitiveness by -0.2. Except from actions *f* and *g*, all others can be selected multiple times (for instance, change the product quality 3 times, affecting a total of -0.6 in price competitiveness and improving product quality in 1.2, at a fixed cost of $ 120.000). Also, actions *d* and *h* can take negative values (decrease product quality and increase price, respectively).

If a company has an extensive list of possible actions as shown in Table 1, it is possible to optimize the portfolio in order to increase the company's gross profit. For the examples described in this work, it is assumed that the product has the following characteristics:

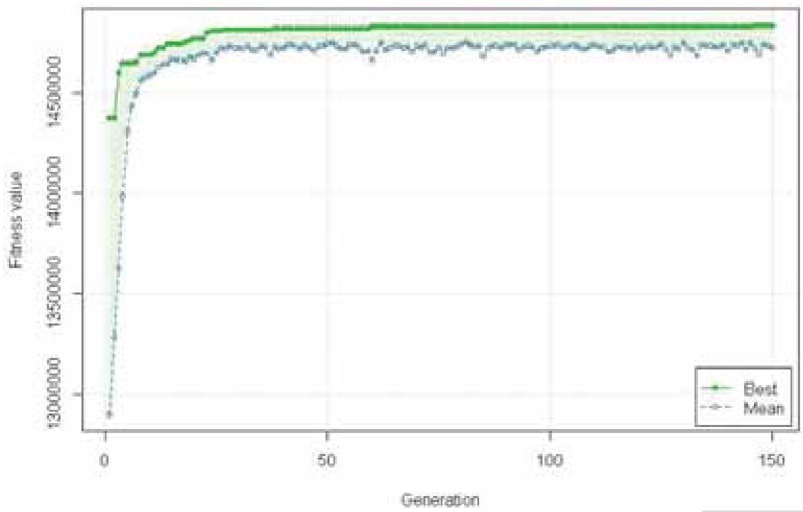
- Cost of $ 700;
- Price ranging from $ 1250 (lower Competitiveness) to $ 750 (higher Competitiveness)
- Market Size: constant 100 000 units/ year

The optimization algorithm chosen in this work is a binary genetic algorithm, available in the "GA" R package described in Scrucca (2013). Due to the fact that optimization method is binary, the input of this optimization is not compromised of only the 8 itens of Table 1, but multiple instances of items that can be chosen multiple times, as well as negative instances of itens *d* and *h*.

The objective function to be maximized is the gross profit: *GrossProfit = MarketSize x (ProductPrice - ProductCost) x MarketShare.*

### 2.3.1 Optimal portfolio with unlimited resources

Initially, the case with unlimited resources is considered. Using the genetic algorithm with 150 iterations, population size of 50, crossover and mutation probability of, respectively, 80% and 10%, the results presented in Figure 5 were obtained.




| Action | Advert. |
|---|---|
| a. Invest on specialized media 1 | +4 |
| b. Invest on specialized media 2 | +4 |
| c. Invest on specialized media 3 | +4 |
| d. Change product quality | 0 |
| e. Increase Payment Flexibility | 0 |
| f. Agreement with logistics provider | Yes |
| g. Acquisition of a new distribution center | no |
| h. Reduce/ Increase Price | +4 |

Figure 5: Genetic algorithm convergence and results (unlimited resources)

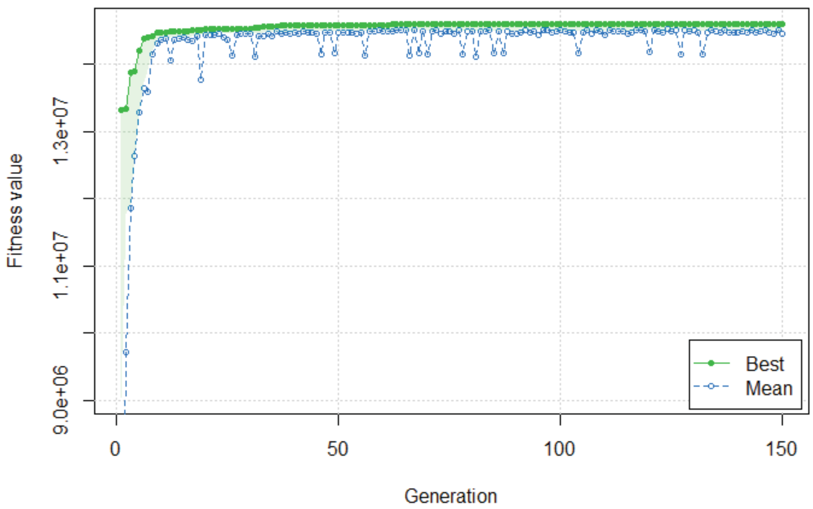
The best gross profit achieved is $ 14,8M, by taking the actions listed in the right side of Figure 5. In short, for this example, the proposed actions were:

- Invest in all specialized media (1, 2 and 3). As per Figure 4, indeed "Company 1" has a very low "Advertisement" value, which results in lower market share, specially for "Persona 1";
- Product Quality and Payment Flexibility should remain unchanged for the maximum gross profit. As per Figure 4, these two values are very high for "Company 1";
- The agreement with logistic provider also brings positive results, as well as reducing price. Note that price competitiveness represents the weakness of "Company 1".

### 2.3.2 Optimal portfolio with limited resources

Now the optimization takes into consideration the limitation in marketing budget of a company and, thus, tries to optimize the portfolio given that the overall cost will not exceed a given value (in this example, $ 12.000). This problem is similar to the classical knapsack problem (Wikipedia Contributors, 2015), but with some modifications: some items can be taken multiple times and some items have 0 cost (but also can have negative impact on the objective function). In the genetic algorithm, this constraint was implemented by subtracting from the fitness function a value proportional to the exceeding budget.

The final result for this simulation can be visualized in the Figure 6:




| Action | Advert. |
|---|---|
| a. Invest on specialized media 1 | 0 |
| b. Invest on specialized media 2 | 0 |
| c. Invest on specialized media 3 | +4 |
| d. Change product quality | 0 |
| e. Increase Payment Flexibility | 0 |
| f. Agreement with logistics provider | Yes |
| g. Acquisition of a new distribution center | No |
| h. Reduce/ Increase Price | +4 |

Figure 6: Genetic algorithm convergence and results (limited resources)

Given the limited resources destined for the marketing strategies, fewer actions could be taken and, thus, it is expected that both cost and total gross profit will be lower than the previous situation. Indeed, the total cost was $ 11k, which is below our limit value. Also, the gross profit of $ 14,6M was slightly lower than in the previous example. In practice, the limited resources barred the investments in actions 1 and 2, affecting the overall value. All other actions remained the same when compared with case described in section 2.3.1.

## 3 Final Comments and Conclusion

This work described a methodology for decision support in the field of marketing strategy optimization, using as input the basic market information, both from competitors and customers. In order to assure that this methodology provides insightful recommendations, it is essential to calibrate the model parameters. However, these can be made more accurate as time passes, using, for instance adaptation mechanisms. In other words, over time, the market share trend should be re-estimated. The marketing actions should be monitored in order to evaluate the effect on market share and customer's perceived value. Any mismatch between the prediction and the real values should be used to re-calibrate the model parameters.

The proposed model could also be used to estimate cross elasticity (Cooper and Nakasishi, 1988), that is, the impact in market share of a company “i” by marketing efforts of a rival company “j”. In this way, potential market threats could be countered.

Many further improvements can be included in this methodology, for instance:

- Test other decision process models;
- The optimization model to support the best marketing strategies can be improved;
- Other factors that could impact decision making could be considered, such as regulatory issues or companies specific policies;
- The uncertainty in the estimative could be accounted for;
- Further investigation of the conjoint analysis could lead to better knowledge on how the customers value each product feature;
- Include time dependencies in the model.

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