Professor Adrian MICU, PhD
E-mail: mkdradrianmicu@yahoo.com
”Dunarea de Jos” University of Galati
Associate Professor Angela Eliza MICU, PhD
E-mail: angelaelizamicu@yahoo.com
Ovidius University of Constanta
Professor Kamer AIVAZ, PhD
E-mail: kamer_aivaz@yahoo.com
Ovidius University of Constanta
Associate Professor Alexandru CAPATINA, PhD
E-mail: alexcapatina@gmail.com
”Dunarea de Jos” University of Galati

THE GENETIC APPROACH OF MARKETING RESEARCH

Abstract. *This paper highlights the original contribution of genetic algorithms to marketing research techniques, by means of the design and development of a marketing decision making tool based on aggregated mathematic models that lead to the maximizing of a company's profit or market share by using genetic algorithms. The mathematical pattern developed encompasses both the function of the demand reaction to different marketing variables and the function of market global demand. Moreover, the genetic algorithms implemented into the pattern provide suitable solutions for optimizing the marketing functions. A software was also designed and implemented in order to configure the genetic algorithm for discovering the most effective decisions, taking into account the restrictions related to the marketing variables embedded into the mathematical pattern.*

Keywords: *genetic algorithm; marketing mix; decision making; market reaction function; promotional expenses.*

JEL Classification: C63, M31

1. Introduction

This article proposes the development of a marketing decision making technique that would lead to finding the marketing values variables that ensures the maximizing of the profit or of the market share of a product by using the genetic algorithm. Thus, first part of the paper is dedicated to the development of a mathematical model that describes the dependency of the market share and of the sale values to the marketing variables, and in the second part of the paper, an optimization problem solving technique by means of genetic algorithms is explained.

The paper emphasizes a mathematical model of the marketing variables' dependency to the market share and the value of the sales in an open economic context as well as in the conditions of the existence of some collections of restrictions. The paper concludes with a series of conclusions and discussions regarding the results provided on a series of simulations, based on a software developed for this purpose.

2. Theoretical Background: Genetic algorithms applied in Economics and Cybernetics

The genetic algorithms describe the evolution of a population of rules, representing different possible beliefs, in response to experience. Rules whose application has been more successful are more likely to become more frequently represented in the population, through a process similar to the natural selection in population genetics.

Genetic algorithms are a class of algorithms working on problems that cannot be solved in a deterministic and analytical manner. The main idea is to continuously generate varying solutions to a problem while combining, mutating and evaluating them.

A research focused on modeling and heuristic solving of practical production scheduling problems emphasizes a Pareto-based genetic algorithm incorporating a local search module, which optimizes a job scheduling problem in the manufacturing field (Zhang et al., 2013)..

A research coordinated by Fu et al., 2013 outlines two different applications of the Genetic Algorithms (GA) in portfolio management, which were implemented in order to determine the optimized parameters setting of different technical indicators and portfolio weighting.

A recent survey developed in the field of stock forecasting (Wei, 2013) reveals the capabilities of a hybrid model, which is based on an adaptive expectation genetic algorithm to optimize adaptive network-based fuzzy inference system for predicting stock price trends.

An optimal mix of genetic algorithms and stochastic simulations represented the core of a research focused on the development of real options market model, which derives the firms' optimal investment and disinvestment thresholds in a competitive environment (Straßburg et al., 2012).

A research focused on the role of genetic algorithms used in the process of solving marketing optimization problems introduces a list of relevant marketing areas to which an optimization technique such as genetic algorithms could be applied (Hurley et al., 1995).

The results of a survey conducted by Kuo et al., 2004 emphasize the role played by clustering analysis and genetic algorithms (GAs) in the processes related to optimal solutions for various complex optimization problems in marketing field.

The findings of a research conducted by Gruca and Klemz (2003) illustrate that a genetic algorithms based procedure, called GA SEARCH, outperforms the best available algorithms designed to solve an optimal product positioning problem. Another relevant research in this field emphasizes a nonlinear mixed-integer programming model and a genetic algorithm that can solve the reverse logistics problem involving product returns (Min et al., 2006).

Two researches focused on Supply Chain Networks draw our attention: a mixed-integer non-linear programming model for multi-objective optimization of SCN and a genetic algorithm approach to solve the problem which was met on a manufacturer from Turkey (Altiparmak et al., 2006) and a model that optimizes a vendor managed replenishment system using machine learning and genetic algorithms (Chi et al., 2007).

In Romania, there were conducted a lot of researches in the field of genetic algorithms. Thus, a study developed in the field of genetic algorithms and simulation as decision support in marketing strategies reveals a GA-SIM integrated system which supports operative management personnel in production planning and marketing strategies (Stoica and Cacovean, 2009). Another study developed by Maries and Dezsi (2011) proposes a genetic algorithm for community formation based on collective intelligence capacity, introducing the concept of intelligence index, aiming to optimal partitions of a set of agents. A very interesting approach outlines the design of a system for evaluation of test data generators, which is used to compare different implementations of test data generators like random or based on genetic algorithms.

3. The structure of a genetic algorithm

The genetic algorithms represent a search technique that copies the evolutionary process of biological systems. The principle consists in the existence of a search space containing solutions (points) that will be found by the genetic algorithm. The algorithm starts by randomly distributing a finite number of points in the search space. Each point in the search space is called the individual and a finite number of points at a given time is called the population. Each individual has an internal representation and the quality of an individual is assessed by the size of qualification (size that reflects the quality of the individual, as the individual is more promising, his classification is greater). The continuous search consists of an iterative process of creating new individuals in the search space by recombining and/or modifying the existent individuals of a population. This is the similarity with the evolutionary process of the genetic algorithms. The algorithms reuse the content of existing individuals in an iteration and a new iteration is called a generation. The recombination or the modification of the genetic material is performed by genetic operators (usually there are two types of operators: crossbreeding and mutation). The crossbreeding operator recombines two individuals (or both parents) from a population to create new individuals (or two heirs) for the next population (or generation). The mutation operator randomly changes parts of the individuals of a population.

A chromosome is formed by concatenating genes. The genes represent the coded values of the variables of the objective function and of the constraints. The encoding of the variables values is up to the user of the genetic algorithm. Then it is generated randomly or heuristically an initial population of chromosomes. For every generation or each step it is measured the compatibility of each chromosome in the population, a higher value may be an indication for a possible better solution. The right chromosomes that inherit the best characteristics of both parents are then selected to produce offspring for the next generation. After several generations the result becomes better and better.

If we are using only the crossbreeding operator to generate offspring, a possible problem that can arise is the fact that if all the chromosomes in the initial population have the same value at a certain position, then all future offspring will have the same value at that position. Since genetic algorithms are stochastic iterative processes, whose convergence is not guaranteed, there must be specified a stopping condition of the algorithm, which can be related to the maximum number of generations or to reaching an acceptable level of "fitness" value. The structure of optimization software can be shown schematically as:

The objective function - $F(x_1, x_2, ..., x_n) \Rightarrow \max. \text{ or } \min.$ (1)

Restrictions:

$$H_1(x_1, x_2, ..., x_n) \le 0$$
$$H_2(x_1, x_2, ..., x_n) \le 0$$
$$H_m(x_1, x_2, ..., x_n) \le 0$$

The evaluation function: $E = F + \sum_{i=1}^{m} p_i G(H_i)$ (2)

where:

p_i - the penalty coefficient, $i = \overline{1, m}$;

$G(H_i)$ - the restriction functions, $i = \overline{1, m}$

The assessment function takes into account the value of the objective function with the values of the respective chromosome to which it is added the restrictions penalty with the weight of their importance (penalty coefficient). Often, it is considered $G(H_i) = H_i^2$ (3)

4. The genetic approach in optimizing the marketing mix of a company

The purpose of this paper is to determine, using the genetic algorithm, the values of the marketing variables, which provide, for a product, the maximization of the profit or of the market share, as appropriate, according to the goals of the analyzed company, during the last months of 2013. In order to provide the expected solutions, we primarily build an aggregate model that expresses the market share and the profit of that product, respectively, according to the partial models for the demand response to different marketing variables of the company and its competitors, as well as according to the global demand estimated of the market from Romania, during the covered time interval.

In order to apply the genetic algorithm for the optimization of the marketing mix, for the studied product, we must first determine their demand response functions for different marketing variables. In order to determine them, we studied the time interval from June 30th 2012 to June 30th 2013. We have found that the marketing variables which may influence the reaction of the market are X, Y and Z, with the following meanings:

X - the price;

Y - the promotional expenses;

Z - the expenses for improving the quality of the product (including the services related to the sale).

We analyzed separately the influence of each variable X, Y, Z upon the product demand. We will explicitly specify within the paper the recorded values, during each season from the analyzed time interval, for the variables X, Y, Z and Q.

The best mathematical function from the statistical point of view and with economic significance for the modeling of the demand response in relation to the price variable, X, has proven to be the best:

$$Q = a_1 X^{a_2} \tag{4}$$

where:

Q - the sales of the product, expressed in physical units;

X - the price of a product, expressed in RON;

a_1, a_2 - the parameters of the model;

By using logarithm in the equation (4) we obtain:

$$\ln Q = \ln a_1 + a_2 \ln X \tag{5}$$

If in the equation (5) we note:

$$Q' = \ln Q$$

$$a'_1 = \ln a_1$$

$X' = \ln X$

we obtain the equation:

$$Q' = a'_1 + a_2 X' \quad (6)$$

For the estimation of the unknown parameters we used the method of the smallest squared numbers, so that we obtained:

$$\begin{cases} a'_1 = \dfrac{\sum Q' - a_2 \sum X'}{n} \\ a_2 = \dfrac{n \sum X'Q' - \sum X' \sum Q'}{n \sum (X')^2 - \left(\sum X'\right)^2} \end{cases} \quad (7)$$

By replacing the values for X’ and Q’, obtained by using logarithm on the values of X and Q during the n seasons of the analyzed time interval, we obtained:

$$\begin{cases} a'_1 = 36.81269 \\ a_2 = -193322 \end{cases}$$

From the previously made notations it results that:

$$a_1 = e^{a'_1}$$

$$a_1 = e^{36.81269}$$

$$a_1 = 9.71735 \cdot 10^{15}$$

Taking into account only the first two decimals of the parameters a_1 and a_2, the equation (4) becomes:

$$Q = 9.72 \cdot 10^{15} X^{-1.93} \quad (8)$$

and it represents the demand reaction model for the studied product according to the price variable. The equation (31) with the price X expressed in thousands of RON (Romanian currency), becomes:

$$Q = 25566.205\, X^{-1.93} \quad (9)$$

In order to evaluate the quality of the determined model we calculate the determination coefficient, R^2, that can be determined using the formula:

$$R^2 = \frac{SSR}{SSR + SSE} \quad (10)$$

Where the sizes that are present have the following meanings:

SSR - The square sum of the adjusted values deviations Q_a, present in the regresion equation, compared to the average $\overline{Q}$;

SSE - The square sum of the errors or the square sum of the observed values deviation Q_i compared to the adjusted values Q_a;

i - the number of observations, $i = \overline{1, n}$.

The equation (10) can also be expressed as:

$$R^2 = \frac{\sum_{i=1}^{n}\left(Q_a - \overline{Q}\right)^2}{\sum_{i=1}^{n}\left(Q_a - \overline{Q}\right)^2 + \sum_{i=1}^{n}\left(Q_i - Q_a\right)^2} \tag{11}$$

For the model in equation (11) we obtain a value very close to 1, which means that a significant part of the variation of Q was explained by the determined function. The determination of this function can be done by strings of values of X and Q, which helps computer systems to determine the best features in statistical terms. We determined functions that modeled even better the evolution of the phenomenon, even with $R^2=1$, but their form was not suitable for the demand-price relationship. The most adequate function after applying the two criteria, the statistical and the economic significance, is the one proposed above.

In order to estimate the demand reaction function, Q, to the promotional expenses, Y, we went on a similar route and concluded that the best model in terms of statistical and economic significance is the model ADBUDG.

ABDUBG models the reaction of the sales within a market at different levels of promotional expenses. This model starts from the following assumptions, regardless of the time interval of the analysis:

- If these promotional expenses are eliminated, the market share will decrease, but there is a minimum value until it can decrease from initial value;
- If these promotional expenses are significantly increasing to a level of saturation, the market share will increase, but up to a maximum acceptable value;
- We define a rate of expenses according to the current market share;
- We can estimate based on data analysis and management judgment, how much the market share will increase following a 20% increase of the promotional expenses.

The ABDUBG model has the following form:

$$Q = a_1 + \left(a_0 - a_1\right)\frac{Y^{a_2}}{a_3^{a_2} + Y^{a_2}} \tag{12}$$

where the parameters a_0 and a_1 represent the highest level of the sales, at maximum promotional expenses, at their lowest level respectively, in the absence of promotional expenses, for a season; the parameters a_2 and a_3 result from other calculations, which will be given below.

The equation (12) can also be written in the following form:

$$Q = \frac{Q - a_1}{a_0 - a_1} = \frac{Y^{a_2}}{a_3^{a_2} + Y^{a_2}} \tag{13}$$

If in equation (13) the numerator and denominator are divided from the term on the right with Y^{a_2} we obtain:

$$Q' = \frac{1}{\left[\frac{a_3}{Y}\right]^{a_2} + 1} \tag{14}$$

Out of the equation (14) we obtain:

$$Q'\left[\frac{a_3}{Y}\right]^{a_2} + Q' = 1 \tag{15}$$

Or:

$$\left[\frac{a_3}{Y}\right]^{a_2} = \frac{1 - Q'}{Q'} = Q_0 \tag{16}$$

If we use logarithm on the equation (16) we obtain:

$$\ln Q_0 = a_2 \ln a_3 - a_2 \ln Y \tag{17}$$

If in the previous equation we make the following notations:

$$Q_1 = \ln Q_0$$

$$A = a_2 \ln a_3$$

$$B = -a_2$$

$$Y' = \ln Y$$

we obtain:

$$Q_1 = A + BY' \tag{18}$$

The parameters A and B from the equation (18) can be obtained by using the method of the smallest squares, thus:

$$\begin{cases} A = \dfrac{\sum Q_1 - B\sum Y'}{n} \\ a_2 = \dfrac{n\sum Q_1 Y' - \sum Q_1 \sum Y'}{n\sum (Y')^2 - \left(\sum Y'\right)^2} \end{cases} \tag{19}$$

Within the formula (19), n is known and it represents the number of seasons from the analyzed time interval, Y' is obtained by using logarithm for the value of promotional expenses during each season, and Q_1 is given by:

$$Q_1 = \ln \frac{1 - Q'}{Q'} \tag{20}$$

Or:

$$Q_1 = \ln \frac{1 - \frac{Q - a_1}{a_0 - a_1}}{\frac{Q - a_1}{a_0 - a_1}} \tag{21}$$

Within the formula (21), the size Q represents the demand, respectively the number of products sold by the studied company in every season from the studied time interval. The parameters a_0 and a_1 were estimated to have values $a_0=15$ and $a_1=260$ pieces. The measure of a_1 was determined at the maximum production capacity of a company for a season without resorting to cooperation, so accepting the idea that at maximum promotional expenses we can sell everything it can produce.

Taking into account the previously made notations, we obtain the function:

$$Q = 15 + (260 - 15)\frac{Y^{1.8404}}{\left(e^{14.7908}\right)^{1.8404} + Y^{1.8404}} \tag{22}$$

In order to convert the static model of the demand response, Q, according to the promotional expenses Y, denominated in RON, in a dynamic model, we replaced the function h with the function from the relation (22):

$$Q_t = b_1\left[15 + 245\frac{Y_t^{1.84}}{e^{27.22} + Y_t^{1.84}}\right] + \mu Q_{t-1} \tag{23}$$

By using the equation (23) for different seasons from the analyzed time interval, we obtained the following values:

$\mu = -2$

$b_1 = 1.33$

With these values, the equation for the demand during the season t becomes:

$$Q_t = 1.33\left[15 + 245\frac{Y_t^{1.84}}{e^{27.22} + Y_t^{1.84}}\right] + 0.2Q_{t-1} \tag{24}$$

Since μ has a negative value, the dynamic effect upon the sales period is practically negative, important being the ongoing activities ($b_1=1.33$). This dynamic model was tested statistically and it has $R^2=0.99$. If the values of the sales are replaced with these ones from the previous season Q_{t-1} we obtain the equation for the future demand Q, having the shape:

$$Q = 2.52 + 325.85\frac{Y_t^{1.84}}{e^{27.22} + Y_t^{1.84}} \tag{25}$$

where Y represents the value of the future promotional expenses for the studied product. To determine the demand response model Q, based on the expenses incurred for improving the quality, Z, including also the services attached to the sale of products, expressed in thousands of RON, we used the software Logistep Graphxy and we obtained:

$$Q = 48.3072 + 4.37284Z - 0.0396393Z^2 \quad (26)$$

This function has a determination coefficient R^2 at a value very close to 1, so the determined function is good.

With the demand response functions determined for each marketing variable in order to use the market share model, we have to further analyze the competitors of the commercial company. The main competitors have together with the studied company over 90% of product sales in our country. We analyzed the situation and the evolution of the sales and of the market share for each individual competitor, during the time interval 2012-2013, which was the basis for the aggregate reaction model of the marketing mix. We have examined and compared the levels of the marketing variables X, Y, Z in each case. We allowed the same types of demand reaction functions to the three variables and in the case of the major competitors as well as for the studied company. We estimated the average market competitor whose marketing variables X_m, Y_m, Z_m have the values calculated in an open manner, described in the previous paragraph as an arithmetic average of the values of the variables of the three main competitors. The average efficiency of the competitors is determined as an arithmetic average of the individual scores, obtained according to their market share compared to the market share of the studied company, as shown in the previous section and has the value K_m=3.7.

The parameters a_1, a_2, a_3 were determined taking into account the different market shares of the average competitor and of the studied company as well as the evolution of their marketing variables X, Y and Z, for the analyzed time interval, adapted to the given situation, their sum being equal to 1. We obtained the following values: a_1=0.1, a_2=0.65, a_3=0.25.

As from one period to another great changes have taken place in the market share level of the studied company, we preferred not to give the market share during the time interval t in relation to the time interval t-1, but only according to the marketing variables of the company and of the competitors.

One issue still to be resolved concerns the estimation of the marketing variables used by the competitors, during the last six months from the analyzed time interval. Calculating the values of the marketing variables of the average competitor X_m, Y_m and Z_m, during the season previous to the predicted one, that in the last six months of the year 2012, we obtained compared to the values of the marketing variables of the studied company, the following results: X_m=1.1X, Y_m=6Y, Z_m=6Z.

We have given a probability of 0.5 as in the next six months, in order for the competitors to keep their prices and promotional expenses at the same level and a probability of 0.5 so they would react to the changes of the prices and promotional expenses of the studied company in the same manner as in the past.

This aspect can be given by the following equations:

$$X_{mt} = 0.5(X_{mt-1}) + 0.5(1.1X_t) \quad (27)$$

$$Y_{mt} = 0.5(Y_{mt-1}) + 0.5(6Y_t) \quad (28)$$

or

$$X_{mt} = 0.5(1.1X_{t-1}) + 0.5(1.1X_t) \quad (29)$$

$$Y_{mt} = 0.5(6Y_{t-1}) + 0.5(6Y_t) \quad (30)$$

where:

X_{mt}, Y_{mt} - the price and the promotional expenses of the average competitor during the time interval t.

X_{mt-1}, Y_{mt-1} - the price and the promotional expenses of the average competitor during the time interval t-1.

X_t, Y_t - the price and the promotional expenses of the studied company during the time interval t.

X_{t-1}, Y_{t-1} - the price and the promotional expenses of the studied company during the time interval t-1.

By substituting in the relations (29) and (30) the known sizes X_{t-1} and Y_{t-1}, expressed in thousands RON, and giving up the clues expressing time interval in order to simplify the formula, we obtain:

$$X_m = 9.79 + 0.55X \quad (31)$$

$$Y_m = 4.98 + 3Y \quad (32)$$

where the sizes above have the following significance:

X, Y - the values of the marketing variables of the studied company, searched and provided by the genetic algorithm;

X_m, Y_m - the values of the marketing variables of the average competitor, including its reaction to the changes of the marketing variables of the studied company.

Thus, in a similar manner, we obtain:

$$Z_m = 0.9(6 \times 9.15) + 0.1(6Z) \quad (33)$$

or

$$Z_m = 49.41 + 0.6Z \quad (34)$$

where:

Z - the expenses with improving the quality of the products made by the studied company, whose value results from using the genetic algorithm.

Z_m - the expenses with improving the quality of the products, in the case of the average competitor, including its reaction to the changes made by the studied company.

In order to estimate the mathematical model of global demand evolution for the studied product, VP, in connection with the variable price, we started from the following equation:

$$VP = K\left(\frac{X + X_m}{2}\right)^{-1.93} \quad (35)$$

where the constant K will be determined based on data from the past analyzed time interval, and the price is considered as an arithmetic average of the price of the average competitor from the market, X_m (the price can be calculated as a weighted average).

After we made the calculations the following equation resulted:

$$VP = 8.96 \cdot 10^{17}\left(X + X_m\right)^{-1.93} \quad (36)$$

In which the price is expressed in RON.

The sales of the market in the same season of the last year, meaning the first months of 2012 were X. According to the annual market growth rate we can estimate the sales in the first months of 2013 to about 2665.

A complex function for estimating the global demand, VP, in which it is given a weight of 0.9 to the estimated demand based on previous data and a weight of 0.1 to the estimated demand based on the price variable has the form:

$$VP = 0.1 \times 2.35672 \cdot 10^{6}\left(X + X_m\right)^{-1.93} + 0.9 \times 2665 \quad (37)$$

where X and X_m represent the price of the studied company and the price of the average competitor respectively.

By replacing the global market demand function given by the relation (37) in the X_m equation given by the relation (27) we obtain:

$$VP = 235672\left(9{,}79 + 1.55X\right)^{-1.93} + 2399 \quad (38)$$

In order to write the model of the profit we need to know the total fixed expenses, which shall be taken into account the expenses necessary for the production as well as the expenses related to the promotional activity and the improving the overall quality of the studied products, over a time interval. For the last six months of 2012, the fixed costs with the production of the products were of 431 000 RON and the unit variable costs for an equivalent product C_{uv}=10.387 RON. For the first six months of the year we have admitted a possible increase, according to the inflation rate estimated during this time interval and other elements, so that they can be estimated at 474 000 RON and C_{uv}=11.300 RON respectively.

5. Design of a software based on genetic algorithms' implementation in the marketing research

The section presents the functionality and the results obtained by means of a software especially designed and developed for this purpose. It allows defining the functions of market reaction, configuring the genetic algorithm and its execution in order to reach the values of marketing variables necessary to attain the established objectives. The objectives are represented by the maximization of the demand, and the marketing variables consist of: Price, Promotional expenses and Sales improvement expenses (transport, installation, guarantee etc.)

The application is structured into three parts and focuses on defining the functions of market reaction, on the restrictions related to the three variables mentioned above and on configuring the genetic algorithm for discovering the optimal values.

In the first part of the configuration interface, the user has the option to define de values of the variables describing the functions of reaction. Graphxy application generates the highest values for the variables of the considered equation. These values are imported back to our application.

The following variables were established, as a structure of the function of reaction:

- The marketing variable *Price* – the reaction of the market is the one suggested by the equation;
- The marketing variable *Promotional expenses* – the market's reaction is indicated by the equation (ABDUBG model);
- The marketing variable *Sales improvement* – the market's reaction is indicated by the equation.

Before sending it to be processed by Graphxy application, the function of market reaction for promotional expenses or ABDUBG model needs to be processed in order to become a structure of equations accepted by Graphxy. Figure 1 presents the interface available for the user to configure the functions of market reaction.

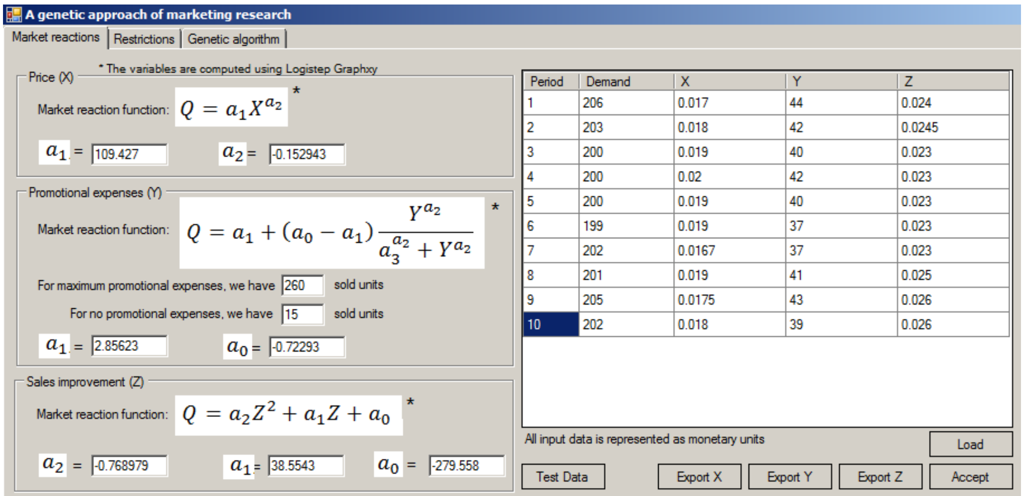

Figure 1 – Defining the equations of reaction for the three marketing variables considered

In the case of promotional expenses, the variables a_0 and a_1 do not refer to the ones within ABDUBG model; they are used in processing unknown variables within the function of reaction.

In case of lack of restrictions, the application will generate values for each marketing variable, at the necessary level for reaching the specified demand, without considering the subordination that might appear between these variables. Figure 2 illustrates the available options in this case.

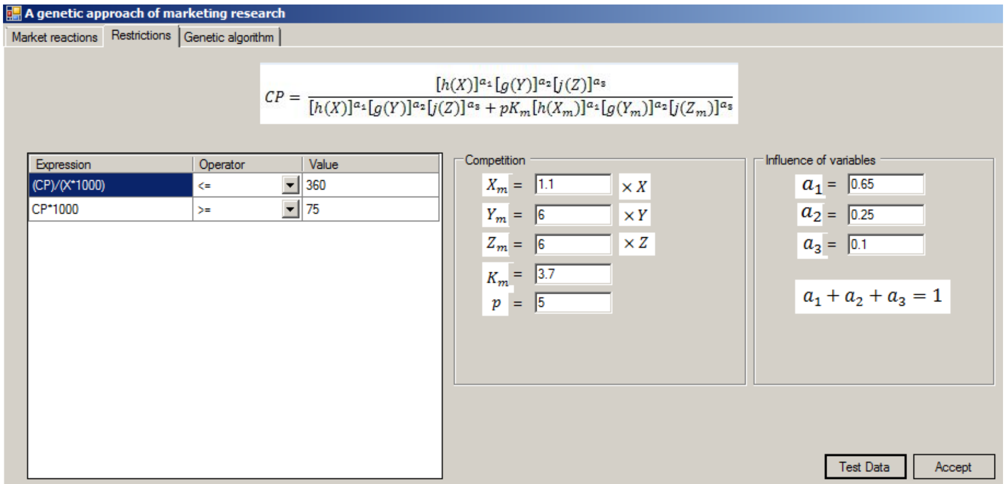

Figure 2 – Interface that can be accessed to define restrictions of marketing variables

The values related to medium competitor are estimated by the user and obtained further to a careful analysis of the market and the competitors, in order to be able to find out: the relations between the very own marketing variables and the medium ones on the market, the coefficient of the competitors' medium efficiency (it is found out as an arithmetic average of individual points got as a result of their market share, compared to the one of the studied company) and the number of the direct competitors of the analyzed company.

Furthermore, there is the possibility of defining the degree of influence of each variable at the level of the demand under value form. As a result of the fact that sales are expressed as a multiplicative equation, the influence is represented by sub-unitary values considered to be exponents for each of the three equations of market reaction. The interface allows defining an unlimited number of restrictions, all of them being expressed by of marketing variables and market share. The defined restrictions refer to the number of products that can be offered by the company, as well as to the minimum percentage of the market share.

The genetic algorithm will take them into account when setting the optimum level of marketing variables for the desired demand.

The last page of the application's interface refers to the configuration of the genetic algorithm. According to figure 3, the configuration consists of:

- Setting the number of generations;
- Setting the dimension of a generation or the dimension of the population;
- Setting the mutation rate or the probability of having a solution subject to the operation of mutation;
- Setting the crossbreeding rate or the probability of having a solution subject to the operation of crossbreeding;

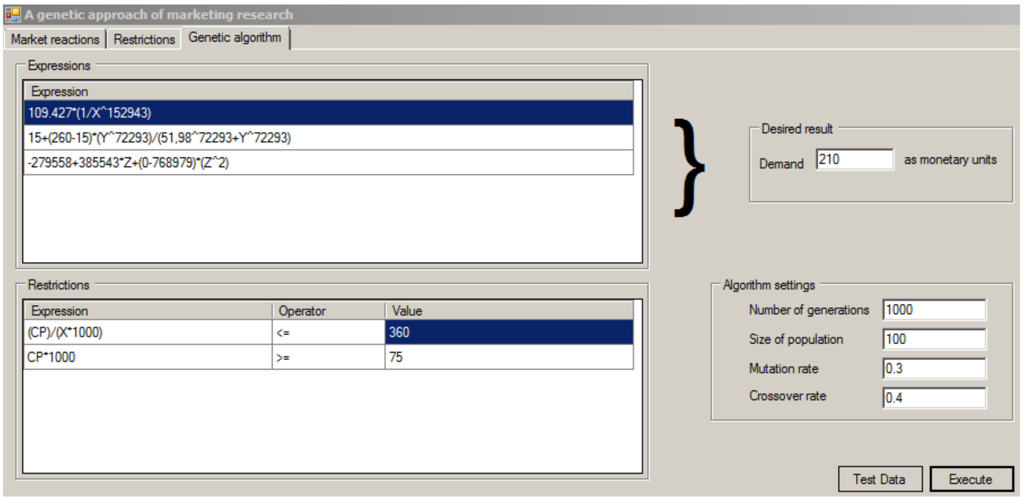

Figure 3 – The configuration interface of the genetic algorithm

Within this stage, it is also possible to visualize the expressions of market reaction and of the restrictions, both being set in the previous pages of the application. The most important aspect of this interface consists of the section of defining the numeric level of the demand, expressed in thousands of RON. In order to run the algorithm on the established values and expressions, the "Execute" button can be applied.

6. Discussions, conclusions and further research

The tests of the application were split into two categories. In the first part, the application was run without any restrictions, setting as an objective of the demand a value among the analyzed periods. This scenario was approached in order to check the accuracy of the results received back. After a series of successive tests, the values of the three variables were approximately equal to the ones of the periods for which the demand is identical with the established objective. To be mentioned the fact that, in case of lack of restrictions, the value of each and every of the three variables is independent. This indicates that approximation, not equality, compared to the variables of the analyzed periods is imposed by the fact that the values are identified as having a major influence on the demand, thus ignoring the variation of the other marketing variables.

If the desired demand is higher than the average of the analyzed periods, the level of the latter marketing variables will be considerably higher than the values of the demand which is closest to the desired value. The explanation can be found in the previous paragraph; it indicates that a high level of demand can be reached by a high level of promotional expenses and respectively for improving sales. In the case of a lower demand, the values of these two variables will be lower, as in the lack of restrictions, it is considered that its value is the only one that can impose such a reduction.

The second stage of the tests consisted of configuring the restrictions visible in figure 3. These restrictions impose a capacity of production below 360 products and a percent of minimum 7.5% of the market share. Once defining these restrictions, the values obtained as a result of simulations were very close to the ones from the analyzed periods. This is explained by the fact that the values resulted from the genetic algorithm are also tested in terms of the expressions within restrictions; as a result of the fact that restrictions describe the dependency of marketing variables, the values of the optimum result are subordinated ones to the others. The existence of restrictions makes possible avoiding the scenario where the variation of a marketing variable is individually capable of changing the level of the demand in the desired way and the three variables cooperate in order to reach to the expected result. The average of participation of each variable at the level of the demand is influenced by the level of participation of the variable in reaction to the demand.

The second category of tests have been run with demand levels other than the ones within the time frame analyzed, especially since these tests have initially shown the accuracy of the results that were sent back.

A series of tests have been run in order to check if the changes influencing each variable on demand affect the results obtained. In the context of an increase of desired sales, the following coefficients of participation were initially considered: 0.65, 0.25, 0.1. The result obtained indicated a significant variation of the price variable and directly proportional for the other variables. Another simulation consisted of switching these coefficients; the results obtained present a higher variation of the value of improvement expenses while the values of the other variables are decreasing, the price variable having the lowest influence.

Simulations were made using different values for the time frames under analysis and for different periods of time subject to analysis. Further to these, it can be noticed that the most realistic are returned for a number of over 7- periods of time. The explanation resides in the fact that Graphxy returns the most accurate values for the variables of the functions only when it has enough data from which to extract the optimal values of the variables. The objective of these simulations was to analyze the results obtained in the context of changing the desired demand

and the defined restrictions. In terms of observations, to be recognized the subordination between the accuracy of the results and the accuracy of the previous analyses. In the context of a higher demand, the marketing variables react depending on the way they had reacted in the previous periods of time at different demand levels.

The higher the number of the accepted generations, the better is the obtained result. This fact represents a limitation of genetic algorithms. Consequently, the obtained result is the closer to reality the higher the number of created generations. For most of the tests that have been run, the algorithm was set as having 1000 generations, a population of 100 members and various probabilities of mutation and crossbreeding. The different variations of these probabilities suggested that a higher probability of mutation leads to a faster input as far as results are concerned. In the case of the developed application, the chromosome has not been binary represented but as a collection of 3 real values, for which:

- The mutation consists of generating a random value for one of the three possible solutions.
- The crossbreeding consists of randomly choosing two chromosomes and switching the values of the same marketing variable between them.

The main advantage of genetic algorithms consists of the fact that they are very suitable for optimizing the functions of continuous variables, of discrete variables or of both types of variables.

In the case of the performed application, there was established that a higher number of products could be sold for higher promotional expenses and especially for improving quality, as compared to the last months of 2012, thus existing the possibility of getting significant profit.

As a future area of research, it is expected to implement the functionality of Graphxy in the particular own application and to connect the application to the data base of the company in order to have direct in real time access to the company's data to be analyzed and to the market it activates on. Once implemented such an application might help the marketer to establish the type of politics that needs to be applied for reaching the strategic objectives that had been set.

REFERENCES

[1] **Altiparmak, F., Gen, M., Lin, L. & Paksoy, T. (2006)**, ***A Genetic Algorithm Approach for Multi-objective Optimization of Supply Chain Networks.*** *Computers & Industrial Engineering*, 51(1), 196-215;

[2] **Arifovic, J. (1994),** ***Genetic Algorithm Learning and the Cobweb Model.*** *Journal of Economic Dynamics and Control*, 18(1), 3-28;

[3] **Chi, H. M., Ersoy, O. K., Moskowitz, H. & Ward, J. (2007),** ***Modeling and Optimizing a Vendor Managed Replenishment System Using Machine Learning and Genetic Algorithms.*** *European Journal of Operational Research*, 180(1), 174-193;

[4] **Feil, J. H. & Musshoff, O. (2013)**, ***Modelling Investment and Disinvestment Decisions under Competition, Uncertainty and Different Market Interventions.*** *Economic Modelling*, 35, 443-452;

[5] **Fu, T. C., Chung, C. P. & Chung, F. L. (2013),** ***Adopting Genetic Algorithms for Technical Analysis and Portfolio Management***. *Computers & Mathematics with Applications*, 66(10), 1743-1757;

[6] **Gruca, T. S. & Klemz, B. R. (2003),** ***Optimal New Product Positioning: A Genetic Algorithm Approach***. *European Journal of Operational Research*, 146(3), 621-633;

[7] **Hurley, S., Moutinho, L., & Stephens, N. M. (1995),** ***Solving Marketing Optimization Problems Using Genetic Algorithms***. *European Journal of Marketing*, 29(4), 39-56;

[8] **Kuo, R. J., Chang, K. & Chien, S. Y. (2004),** ***Integration of Self-organizing Feature Maps and Genetic-Algorithm-Based Clustering Method for Market Segmentation.*** *Journal of Organizational Computing and Electronic Commerce*, 14(1), 43-60;

[9] **Maries, I. & Dezsi, D. (2011),** ***A Genetic Algorithm for Community Formation in Multi-agent Systems.*** *Economic Computation and Economic Cybernetics Studies and Research*; *ASE Publishing;* 45(3);

[10] **Min, H., Jeung Ko, H., & Seong Ko, C. (2006),** ***A Genetic Algorithm Approach to Developing the Multi-echelon Reverse Logistics Network for Product Returns***. *Omega*, 34(1), 56-69;

[11] **Stoica F., Cacovean L. (2009),** ***Using Genetic Algorithms and Simulation as Decision Support in Marketing Strategies and Long-term Production Planning***, *Proceedings of the 9th WSEAS International Conference on Simulation, Modelling and Optimization*, Budapest, Hungary, September 3-5;

[12] **Straßburg, J., Gonzàlez-Martel, C. & Alexandrov, V. (2012),** ***Parallel Genetic Algorithms for Stock Market Trading Rules***. *Procedia Computer Science*, 9, 1306-1313;

[13] **Wei, L. Y. (2013),** ***A Hybrid Model Based on ANFIS and Adaptive Expectation Genetic Algorithm to Forecast TAIEX***. *Economic Modelling*, 33, 893-899;

[14] **Zhang, R., Chang, P. C. & Wu, C. (2013),** ***A Hybrid Genetic Algorithm for the Job Shop Scheduling Problem with Practical Considerations for Manufacturing Costs: Investigations Motivated by Vehicle Production.*** *International Journal of Production Economics*, 145(1), 38-52.