Genetic Algorithms for Development of New Financial Products

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Abstract
New Product Development (NPD) is recognized as a fundamental activity that has a relevant impact on the performance of companies. Despite the relevance of the financial market there is a lack of work on new financial product development. The aim of this research is to propose the use of Genetic Algorithms (GA) as an alternative procedure for evaluating the most favorable combination of variables for the product launch. The paper focuses on: (i) determining the essential variables of the financial product studied (investment fund); (ii) determining how to evaluate the success of a new investment fund launch and (iii) how GA can be applied to the financial product development problem. The proposed framework was tested using 4 years of real data from the Brazilian financial market and the results suggest that this is an innovative development methodology and useful for designing complex financial products with many attributes.

***Keywords*:** Genetic algorithms; product design and financial services.

JEL codes: G11; G24; C49.

Resumo
O Desenvolvimento de Novos Produtos (DNP) é considerado como uma atividade fundamental e que possui um impacto relevante no desempenho das empresas. Apesar da relevância do mercado financeiro há uma escassez de trabalhos sobre o desenvolvimento de novos produtos financeiros. O objetivo desta pesquisa é propor o uso dos Algoritmos Genéticos (AG) como um procedimento alternativo para avaliação da combinação mais favorável das variáveis para o lançamento do produto. O estudo almeja: (i) determinar as variáveis essenciais do produto financeiro estudado (fundos de investimento); (ii) determinar como avaliar o sucesso do lançamento de um novo fundo de investimento e (iii) como o AG pode ser aplicado ao problema do desenvolvimento de um novo produto financeiro. O modelo proposto foi testado com o uso de 4 anos de dados reais do mercado financeiro brasileiro e os resultados sugerem que é uma metodologia de desenvolvimento inovadora e útil para o desenho de complexos produtos financeiros com muitos atributos.

***Palavras-chave*:** Algoritmos genéticos; desenvolvimento de produtos e serviços financeiros.

Submitted in November 2006. Accepted in April 2007.

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1. Introduction

Traditionally, the multi-attribute product design problem is divided into two groups: (i) a simple product, which involves the launch of a unique product and (ii) a line of products, when many products are launched simultaneously. The simple product design problem incorporates the definition of the ideal levels of its attributes in order to maximize a target function. As examples of target functions there are the buyer's welfare problem and the seller's welfare problem. The multi-attribute product design problem has been researched for many years. There are many approaches to the subject, showing increasing performance due to the use of intelligent algorithms.

Kohli and Krishnamurti (1987, 1989) showed that the market share maximization problem, by introducing new products with multiple attributes and levels, is NP-Hard (high complexity). They proposed and assessed two heuristic approaches: dynamic-programming and shortest-path heuristics. The dynamic-programming heuristic performed better than the shortest-path heuristic.

Kohli and Sukumar (1990) applied the dynamic-programming heuristic, developed by Kohli and Krishnamurti (1987), using joint analysis for achieving a better computational performance.

Balakrishnan and Jacob (1996) applied GAs to the same problems assessed by Kohli and Krishnamurti (1987, 1989). According to the criteria of optimal results, the GAs performed better than the dynamic-programming heuristic. Shi et al. (2001) reinforced Kohli and Krishnamurti's (1987, 1989) conclusions relating to the NP-Hard characteristics of the product design problem. Given the fact that the exact solution procedures are not known for this class of problem, they developed a hybrid method, based on GAs and achieved better results. Gruca and Klemz (2003) applied GA search and outperformed the best currently available algorithm for the new product positioning problem.

Recently, parallel efforts have been made in the financial area in order to apply intelligent algorithms to financial decisions. These efforts have been focused on: (i) portfolio optimization (Crama and Schyns, 2003, Korczak and Lipinski, 2001); (ii) technical trading rules (Allen and Karjalainen, 1999); (iii) financial predictions and insolvency risk (Mckee and Lensberg, 2002, Vareto, 1998) and (iv) investment recommendations (Li and Tsang, 1999, 2000). According to these studies, the GA is the most used intelligent algorithm method applied to financial decisions, as shown in table 1 below.

As can be seen, the financial product development problem has not been appropriately studied in financial decisions. This work shows that, despite the intangible characteristics of financial products, it is possible to identify operational variables that represent the performance of the financial product in order to use GA, thereby improving knowledge of the financial variables and increasing the chances of success of the new product.

Table 1
Intelligent algorithms applied to financial decisions

Financial decision	Number of works	Intelligent algorithm applied
Portfolio optimization	4	GA (3) simulated annealing (1)
Technical trading rules	1	GA
Financial predictions	1	GA
Insolvency risk	1	GA
Investment recommendations	1	GA

Source: Prepared by the author

Three of the ten largest investment banks in Brazil were researched and their respective development of new investment funds was analyzed. These banks represent 23% of the Brazilian market share (the Brazilian investment fund market is worth around US$ 400 billion) and three different logics when it comes to the new product development process: a private domestic logic, a private foreign logic and a state owned logic. The information was collected from interviews with managers and those responsible for the development of new investment funds. After 8 months of dialogue, 4 semi-structured interviews, 5 people interviewed, a review of Brazilian investment fund legislation and field monitoring of the development process it was possible to understand and describe the current experimentation and test processes carried out in these banks, the main operational variables used to specify an investment fund and what makes the launch of a new investment fund successful. Finally, the product simulator, based on GA, was tested using 4 years of real data taken from the Brazilian financial market in order to develop a fictional investment fund.

This paper is structured as follow. Section 2 describes the new investment fund development process, the main variables and the goals identified. In section 3, an overview of the Genetic Algorithm process and the financial product design problem are described and in §4 the model is formulated and tested. In §5 the conclusions are presented.

2. The Development of New Investment Funds

Technically, investment funds are financial products composed of Government securities and fixed or variable rate corporate bonds, issued by various institutions. Its administration model presents the fund manager, who is responsible for investment strategy, and the investor, who is the owner of a notional fund fraction (quantity of quotas). The investor's profitability is a result of the manager's strategy and the market conditions, as reflected in the quota value. The choice of this kind of financial product is justified for the following reasons: (i) a high level of complexity, allowing for the use of mathematical models for simulation purposes and (ii) a significantly large financial market, around US$ 400 billion, as shown in table 2 below.

Table 2
Brazilian Investment Fund Market Structure (US$ billions)

Category	Net Equity	Participation (%)
Fixed income	346.3	88.7
Stocks	33.6	8.6
Others	10.7	2.7
Total	390.6	100

Source: Brazilian Central Bank - April 2006

The present new investment fund development process of the investment banks we studied can be summarized as shown in Figure 1. In the initial Conception or Idea phase, changes in legislation, legal loopholes and benchmarking are the main sources for the creation of new funds. An example of this are funds tied to inflation-indexed securities, such as the General Price Index (IGPM). In this phase it is usual for people from the bank's product and commercial areas to be involved. The following phase, Concept Assessment, is the responsibility of the product area and is characterized by an initial conceptual evaluation of the fund. An initial design of the fund is produced, with basic specifications, such as: minimum investment, minimum period of investment, channel of distribution (retail branch, Internet), administration fee and, occasionally, performance fee. From then on, an analysis of the historic performance of similar funds is carried out in order to adjust the proposed fund to the institution's global risk-return strategy. Compliance of the fund with current legislation is again evaluated. In the next phase, Internal Evaluation, the characteristics of the proposed fund are discussed with professionals from other areas in the bank in order to achieve internal validation of it. At this moment in time, the fund's specifications are more precisely defined, as are any internal restrictions and any possible operational impacts on the process chain (e.g: who will be in charge of custody, how it will be done and how the daily quota valuation will be calculated). The product's economic viability is estimated, based on the experience of the bank's commercial managers. After this, in the development phase, the legal and marketing arrangements for setting up and publicizing the authorized fund are taken care of. Usually, there are no previous tests to evaluate the chances of success of the launch. Only in special cases, such as those imposed by legislation or special investors (e.g: insurance companies), are launch simulations in specific segments carried out. The last phase, Launch or Publicity, takes 2 or 3 months of assessment of the fund's performance (funds raised, profitability, risk) compared to competitor funds.

The total development cycle varies from 15 to 180 days, split up as follows:

a) Conception / Conceptual Assessment / Internal Assessment - 15 to 90 days

b) Development / Launch - 15 to 90 days

Once the investment fund's portfolio has been defined, which is a long-term decision, the main variables of the product used in the model are as shown in Table 3 below, in accordance with the comments of the managers and current legal requirements. Generally speaking fund managers define the success of a new fund by the amount of money invested in it during a certain period of time (compared with the initial expectation at its launch). This procedure is in accordance with the findings of Storey; Storey and Kelly (2001) who concluded that profit (sustainable over the long term), the increase in sales, customer satisfaction and the efficiency of the process were the main performance indicators for the development of new services among different groups of service companies in Great Britain (including banks). This study on the investment fund industry can be interpreted as follows: profit or return (margin of contribution of the administration fee), increase in sales (increase in net equity), customer satisfaction (risk-return relationship) and efficiency (average time for NPD). Recent trends in bank risk management, as highlighted by the Basle II Agreement, reinforce the necessity for specific tests to improve the reliability of products when they face financial adversity. This aspect is very important to investors, because in Brazil investment funds are not protected by banking insurance.

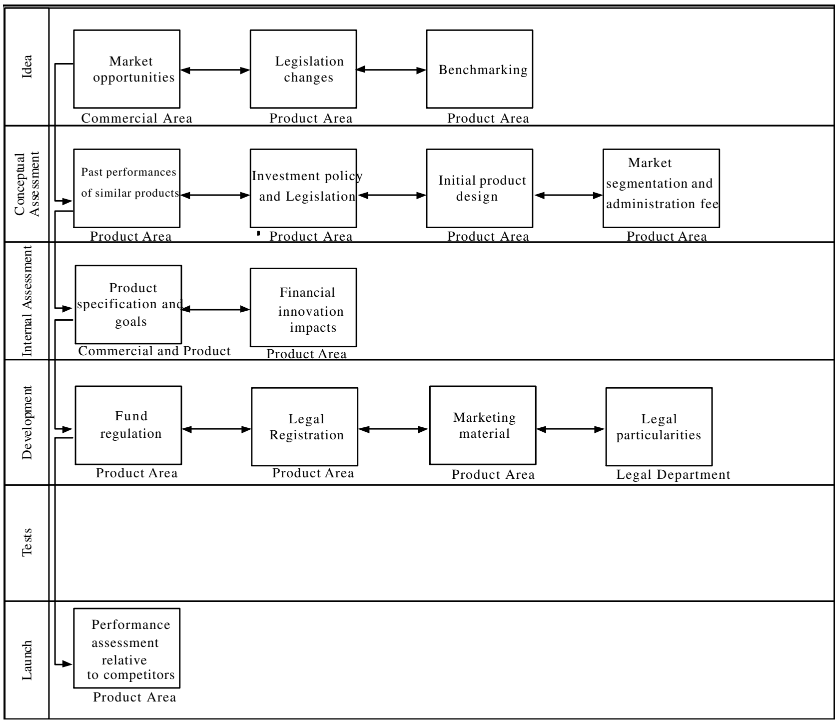

Figure 1
Current new investment funds development process

Table 3
Main variables identified for the investment fund specification used in the model

Variable	Description
Management fee	The main remuneration received by the fund manager. Usually defined as a percentage of net equity.
Performance fee	Eventual payment received by the fund manager because of superior fund performance.
Net equity	The sum of investments plus the value of the portfolio and other receivables, less other expenses.
Conversion period	Period of time between the date of the investment request and the date when the investment is converted into fund quotas.
Withdrawal period	Period of time between the date of the withdrawal request and the date funds are credited to the investor's current account.
Minimum period of investment	Minimum period of time before the first withdrawal may be made.

3. The GA Approach and the Financial Product Design Problem

Genetic algorithms constitute a class of search, adaptation and optimization techniques, based on the principles of natural evolution. The concept of GA was first proposed by Holland (1975). The basis for the algorithm was the observation that a combination of sexual reproduction and natural selection allows nature to develop living species that are highly adapted to their environment. The basic approach is described below (Balakrishnan and Jacob, 1996) and shown in figure 2.

The candidate solution set of strings (i.e., product profiles), generated in Step 1 below, forms the initial chromosome pool (i.e., initial generation). The size of the chromosome (i.e., the number of strings) M is generally maintained in successive generations. The genetic operators used to generate candidate products are:

a) Reproduction: a subset of the product $m\ (< M)$ from the population of size M is selected, based on their fitness and copies of their profiles are generated;

b) Crossover: pairs of reproduced product profiles are chosen and along specific positions on the strings genetic material between the two strings are exchanged leading to offspring (i.e., two new product profiles);

c) Mutation: during the process, a product profile is randomly chosen from the population and the value at a specific location (attribute level) in the string is modified. The fitness function measures the quality of the solution. In an optimization problem, the fitness function simply computes the value of the objective function.

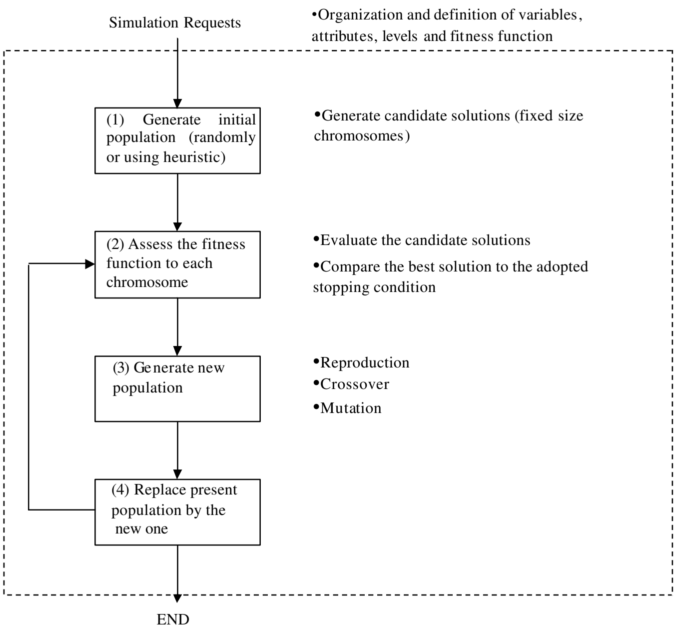

Figure 2
Genetic Algorithm Basic Model

The GA has several advantages such as: (i) the search is conducted at a population of points rather than at a single point, thus increasing the chances of success; (ii) direct use of the fitness function (objective function), thus the candidate product profiles are evaluated, based on the specified objective(s); (iii) it fully evaluates specified candidate solutions, unlike other techniques (dynamic programming), which evaluate profiles sequentially, one attribute at a time. Moreover, GA and other intelligent algorithms (simulated annealing, tabu search) are appropriate techniques for NP-Hard problems.

3.1 The financial product design problem

Generally, the multi-attribute product design problem can be formulated as follow:[1] let $\Omega = \{1, 2, ...K\}$ denote the set of K attributes $K \in \Omega$, let $\Phi_k = \{1, 2, ...J_k\}$ denote the set of J_k levels.

Further, let $\Theta = \{1, 2, ...I\}$ denote the set of I individuals. For individual i, let w_{ijk} denote the part worth of level j of attribute k. Let Θ_1 denote the subset of individuals in Θ whose currently favored (status-quo) brand is offered by a seller seeking to introduce a new brand (product), and let $\Theta_2 = \Theta - \Theta_1$ denote the subset of individuals for whom the status-quo brand is offered by a competitor. Let j_{k^*}

[1] The following mathematical representation is in accordance with Kohli and Krishnamurti (1987).

denote the level of attribute k that appears in the product profile of the status-quo brand for individual i. Then

$$c_{ijk} = w_{ijk} - w_{ij_k^* k}$$

denotes the part worth of level j of attribute k relative to the part worth of level jk^* of attribute k for individual i. Let μ_{ip} denote the part-worths utility of product-profile p relative to the part-worths utility of the status-quo brand for individual i. Then μ_{ip} has a value equal to the sum of c_{ijk} across all levels of all attributes that appear in product-profile p. The share-of-choices for a test profile is defined as the fraction of the number of individuals in Θ who choose it over their status-quo brand. Because the number of individuals in Θ is a constant, identifying a product profile $p*$ that maximizes the share-of-choices is equivalent to maximizing the number of individuals in Θ for whom $\mu_{ip*} > 0$.

By analogy, the financial product design can be understood as a set of K attributes (the main variables identified in §2) $K \in \Omega = \{1, 2, ...K\}$ with a set of J_k levels $J \in \Phi_k = \{1, 2, ...J_k\}$ (e.g.: management fee between 0.3% and 4.5% per year). According to the manager's decisions, the appropriate fitness function (objective function) is the following equation (Hillier and Lieberman, 1980):

$$minimize Z = \sum_{k=1}^{n} \left| \sum_{j=1}^{n} c_{jk} x_j - g_k \right| \tag{1}$$

$g_k =$ goal (increase of net equity, manager's return, financial risk, investor's profitability);
$c_{jk} =$ coefficient;
$x_j =$ variable of decision (net equity, management fee, performance fee, conversion period, withdrawal period, minimum period of investment).

The above equation, a multiple-objective function, represents the minimum sum of variations in relation to the defined goals.

4. The Proposed Framework

The proposed framework is divided into two major parts: (i) a product simulator, which involves the main variables and the goals identified during investigation of the product development process and (ii) a market simulator which includes historical scenarios, in extreme and divergent situations, including the product's life-cycle divided into the launch and maturity periods and with economic turbulence (financial crises) or without it.

4.1 Product simulator

The increase in net equity C during a certain period of time n due exclusively to the result of daily investments and withdrawals Δm from an initial net equity P_0 at t_0 can be formulated as:

$$C_n = P_0(1 + \Delta m_n) \tag{2}$$

Due to the influence of a minimum period of investment, equation (2) can be formulated as:

$$C_n = \left\{ P_0 \left[\prod_{i=1}^{n} (1 + m_i * F_i) \right] - M_c \right\} \tag{3}$$

The factor F_i assumes values 0 or 1 reflecting the influence of a minimum period of investment whose positive impact on the fund's net cash flow m (the result of daily investments and withdrawals) avoids daily withdrawals during the bonus period (the investors do not want to lose their bonus) increasing (or not decreasing) the net equity. The efficiency of the net equity accumulation process can be measured by deducting the pre-established accumulation goal M_C.

Usually, when the investor requests a withdrawal his profitability is influenced by the annual management fee t_a, and by the withdrawal period d_r. Assuming Rp_i as the fund profitability at i (this information can be obtained by past data from similar funds launches), d_u as the number of working days per year and i_b as the benchmark rate (or the opportunity cost during the withdrawal period, the investor's profitability R_{inv} is given by the following equation:

$$R_{inv} = \left[\sum_{i=1}^{n} Rp_i - (1 + t_a)^{(1/du)} \right] - (1 + i_b)^{(dr/du)} \tag{4}$$

According to the category of the fund, there is a performance fee representing the superior performance, when compared to a benchmark rate (e.g.: interest rate), achieved by the manager's fund strategy. Considering that the performance fee t_p occurs only if the fund's profitability exceeds the benchmark rate i_b, then the full investor's profitability equation is:

$$R_{inv} = \left[\sum_{i=1}^{n} Rp_i - (1 + t_a)^{(1/du)} - \sum_{i=1}^{n} t_p \max(Rp_i - i_b, 0) \right] - (1 + i_b)^{(dr/du)} \tag{5}$$

The fund manager's profitability L is a result of the sum of the contributions of the management fee t_a, and the performance fee t_p minus the bonus Ca paid to the investors who did not withdraw during the minimum period of investment d_{ca}, minus the total cost CT (fixed plus variable) and minus taxes IR as given by the following equation:

$$L = \left(\left(\sum_{i=1}^{n}(1+t_a)^{\frac{1}{du}} + \left(\sum_{i=1}^{n} t_p \max\left(Rp_i - i_b, 0\right)\right)\right) P_i\right) - \left(Ca\left(\sum_{i=d_{ca}}^{n+d_{ca}} P_{i-d_{ca+1}} - P_{i-d_{ca}}\right) - CT - IR\right) \tag{6}$$

According to the Basle II Agreement and the risk management procedures adopted by the banks we studied, the value at risk (VAR) of the fund's daily incomes with a standard deviation σ, an initial investment W_0 during a period of time Δt is given by the following equation (Jorion, 1997):

$$VAR = 1,65\, W_0\, \sigma\, \sqrt{\Delta t} \tag{7}$$

The aim of the proposed model is to achieve a good solution, by balancing the defined multiple objectives. In order to achieve impartial results and to align manager and investor interests all goals were considered equally important. The goals were defined in accordance with those of similar funds that have been launched and from the comments of managers. As an example, the range and level of attributes can be obtained from present market values as shown in Table 4 below. Considering M_V, M_L, M_R as the investor's goal, the manager's return goal and the fund's risk goal, respectively, then, the final expression of equation (1) , in accordance with (3), (5), (6) and (7):

$$\begin{aligned}
MinZ = &\Big|\frac{1}{M_C}\Big[P_0\Big[\prod_{i=1}^{n}((1+m_iF_i))\Big] - M_C\Big]\Big| + \\
&\Big|\frac{1}{M_V}\Big[\Big[(\sum_{i=1}^{n} Rp_i - (1+t_a)^{(1/d_u)}) - (\sum_{i=1}^{n} t_p \max(Rp_i - i_b, 0)\Big] - \\
&(1+i_b)^{(d_r/d_u)} - M_V\Big]\Big| + \\
&\Big|\frac{1}{M_L}\Big[\Big[(\sum_{i=1}^{n} P_i(1+t_{ai})^{(1/d_u)}) - (\sum_{i=1}^{n} P_i(t_p \max(Rp_i - i_b, 0))) - \\
&\Big(Ca\Big(\sum_{i=d_{ca}}^{n+d_{ca}} P_{i-d_{ca+1}} - P_{i-d_{ca}}) - CT - IR\Big)\Big] - M_L\Big]\Big| + \\
&\Big|\frac{1}{M_R}\Big[1,65\, W_0\, \sigma\, \sqrt{\Delta t} - M_R\Big]\Big|
\end{aligned}$$

subject to:

$P_0 \leq P_{0\ max}$ (maximum initial net equity, in accordance with similar funds launched and the chosen scenario);
$d_r \leq 5$ (withdrawal period in days, in accordance with to the Brazilian legislation);
$d_c \leq d_r$ (withdrawal period longer than conversion period);
$d_{ca} \leq 4$ (minimum market period of investment less than 4 months);
$t_a \leq t_{amax}$ (maximum market management fee in accordance with table 4);
$t_p \leq t_{pmax}$ (maximum market performance fee in accordance with table 4. Fixed income funds have no performance fee);
$min(\overset{n}{\underset{i=90}{Pi}}) \geq P_{min}$ (minimum legal net equity required, in accordance with Brazilian legislation).

To better illustrate the complexity of the multiple-objective function, for two attributes (P_0, t_a) with each attribute having 7 levels it can result in the search domain shown in Figure 3. The total number of possible product profiles in the large data sets came to 3,048,192 (42x42x32x3x3x6). Moreover, in realistic and dynamic applications, as the number of attributes and levels increases, the number of possible product profiles increases dramatically and it becomes unfeasible to obtain an optimal solution in a reasonable amount of time (Balakrishnan and Jacob, 1996). A mathematical analysis of the complexity of the objective function is presented in the Appendix.

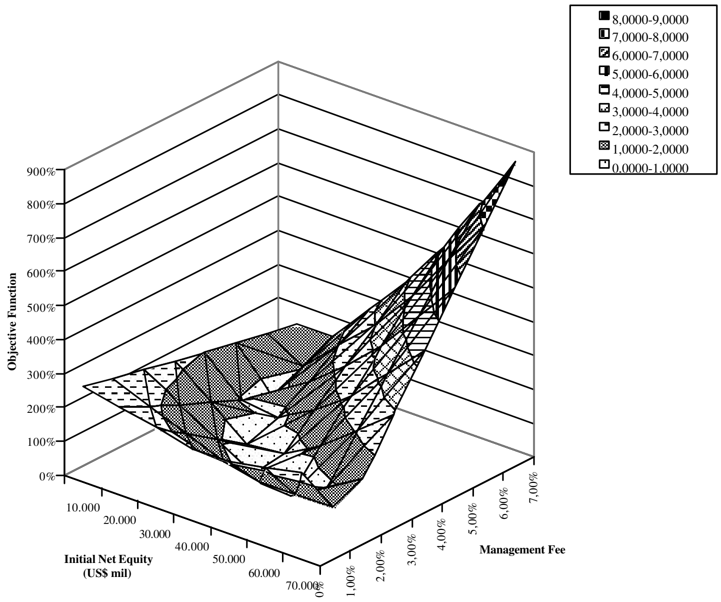

Figure 3
Objective function for two attributes and seven levels

Table 4
Range of attributes

	Administration fee (% per year)		Net Equity (US$ billions)		Withdrawal Period (days)		Conversion Period (days)	
Bank	mín.	max.	mín.	max.	mín.	max.	mín.	max.
Bank of Brasil	0.50	4.50	0.02	1.50	D+ 0	D+ 0	D+ 0	D+ 0
Boston	0.50	3.00	0.01	1.39	D+ 0	D+ 0	D+ 0	D+ 0
Bradesco	0.30	4.50	0.12	0.65	D+ 0	D+ 0	D+ 0	D+ 0
HSBC	0.50	3.50	0.01	1.15	D+ 0	D+ 0	D+ 0	D+ 0
Itaú	2.50	4.00	0.06	2.15	D+ 0	D+ 0	D+ 0	D+ 0
Santander	0.50	4.00	0.05	0.27	D+ 0	D+ 0	D+ 0	D+ 0
Unibanco	1.25	4.00	0.08	0.75	D+ 0	D+ 0	D+ 0	D+ 0
General	0.30	4.50	0.01	2.15	D+ 0	D+ 0	D+ 0	D+ 0

Source: Prepared by the author.
Source: Brazilian investment funds available on the Internet D = day of investor's request.

4.2 Market simulator

The selected historical scenarios contain a diversity of situations including a financial crisis such as: the Asian crisis (1997), the Russian crisis (1998) and the Real crisis (devaluation of the Brazilian currency in January 1999) and non-turbulent periods (October 2002 to February 2004). Furthermore, the scenarios were divided according to product life-cycle and market volatility. The product's life-cycle was divided into two parts: birth (from the beginning to the third month) and maturity (from the forth month on). The volatility was divided into with or without economic turbulence. The four groups of test scenarios are: (a) birth, under favorable conditions, with no economically turbulent maturity phase; (b) birth, under favorable conditions with an economically turbulent maturity phase; (c) birth, under unfavorable conditions. with no economically turbulent maturity phase and (d) birth, under unfavorable conditions with an economically turbulent maturity phase.

The daily flow of investments and withdrawals for each scenario can be obtained by past data for similar funds launched by the institution, or competitors. These flows reflect the investor's behavior under similar conditions for each test scenario. As an example, figure 4 below shows the daily flow of investments and withdrawals of a similar fund launched under the same conditions as scenario C (Brazilian Investment Bank Association - Anbid).

The tests are done using the described product simulator in order to achieve the optimal values of the variables in accordance with the chosen scenarios The purpose is not to predict the future, but assess product performance under controlled situations in order to evaluate its operational limits. This procedure is in accordance with many industrial product development processes (automobile industry, petroleum industry) and other studies (Sirri and Tufano, 1998, Thomke, 1998, Elton et al., 2003, Abensur, 2006).

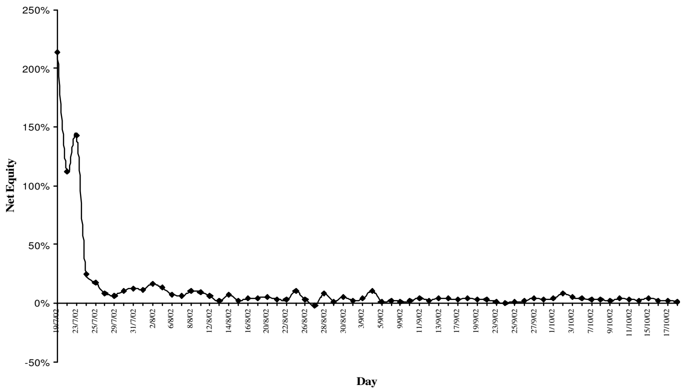

Figure 4
Net equity evolution of a similar fund

4.3 Results

The objective of the proposed model is to evaluate the most favorable combination of variables in order to minimize the variations in relation to the defined goals. The professional GA software Evolver® was used to obtain the results.

According to the GA terminology, if a product has k attributes and each attribute $j(= 1, ..., k)$ has L_j levels, then the numerical sequence representation will be defined by P positions. Thus, for example, if there are three attributes A1 (withdrawal period), A2 (conversion period) and A3 (minimum period of investment) and each one has 6 levels (0, 1, 2, 3, 4, 5), a possible representation (chromosome) would be 5 1 3 which means a withdrawal period of 5 days, a conversion period of 1 day and a minimum period of investment of 3 months.

Once the product characteristics have been defined by attributes and levels, an initial population M was generated randomly. After many attempts a convergence of the results was achieved with the following GA parameters: (i) initial population M = 1,000; (ii) uniform crossover rate = 0.5; (iii) mutation rate = 0.1; (iv) stop condition = 50,000 iterations. The results are presented in Figure 5 and Table 5 below and show the possibilities of success of the new product.

As expected, unfavorable scenarios B and D require higher values of the decision variables than favorable scenarios A and C. The inclusion of legal restrictions enlarges the boundaries of analysis, because the model is not only influenced by market conditions. The withdrawal period of one day in all scenarios shows that it is a useful legal condition to balance the conflicts that exist. From the same perspective, the minimum period of investment of three months is recommendable in scenario B.

The risk goal is fundamental, because it conflicts with every other goal (e.g: higher manager profitability involves higher risks). The simulated management fees are lower than the market management fees, because the model balances manager's and investor's interests with equal weights. The efficiency of the GA can be proved by comparing the simulated initial net equity (13,984.61) with the real case that occurred in the market (13,372.00), a difference of 4.5%.

Table 5
Best results found by GA

	Scenario A	Scenario B	Scenario C	Scenario D
Increase of Net Equity (%)	-0.45	-37.40	-11.29	-57.89
Manager's profitability variation (%)	-0.02	0.03	-0.02	-5.40
VAR (%)	-0.01	0.22	0.12	0.95
Investor's profitability variation (%)	-0.58	-1.81	-0.84	-3.24
Objective Function (%)	1.07	39.46	12.27	67.49
Initial Net Equity (US$)	15,693.59	20,812.70	13,984.61	14,000.00
Management fee (% per year)	2.11	3.38	2.38	4.50
Performance fee (% per year)	0.04	0	0.08	1.03
Withdrawal period (days)	1	1	1	1
Conversion period (days)	0	0	0	0
Minimum period of investment (months)	0	3	0	0

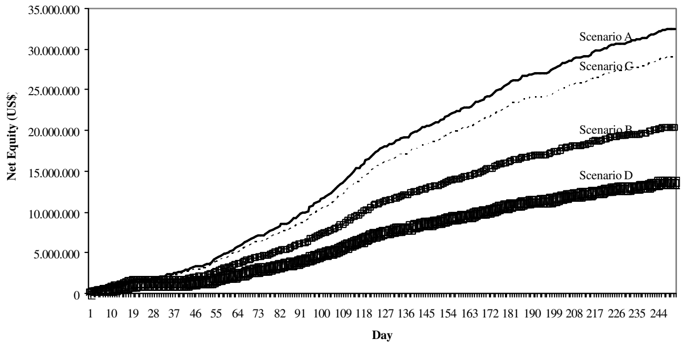

Figure 5
Net equity evolution per scenario

5. Conclusions

The new product development process is a crucial worldwide activity, which separates successful companies from unsuccessful ones. This research presented a general new optimization framework for constructing new financial products, based on Genetic Algorithms (product simulator) and using a scenario technique (market simulator) in order to achieve good solutions for the product design problem. The GA performed as a flexible and fast management tool that can be used in the design of complex financial products (a complete simulation takes less than 5 minutes). Moreover, the flexibility of GA can easily incorporate evolutionary approaches to investor heterogeneity, in accordance with the prospect theory (Kahneman and Tversky, 1979).

Finally, the presence of a structured test stage supported by a simulation tool, as in the industrial development process (automobile industry, petroleum industry), reinforces the team's commitment and team work, thus increasing the synergy between the areas from the beginning (idea) to the end of the development process (launch). This synergy allows for discussion and the improvement of conditions for the launch of the new fund. A simulation tool, as used in industrial development, would improve debate, through a rapid assessment of any possible impact caused by the proposals.

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Appendix

Analysis of the Convexity of the Objective Function

For the category of fund (fixed income) analyzed and considering $n = 2, d_{ca} = 0, F_i = 1p/ \forall i, Ca = 0$ (no minimum period of investment) and $Rp_i - i_{bi} < 0$ $(t_p = 0)$. The variables are: $P_0 = x_1, Ta = x_2$ and $d_r = x_3$, all values are known, positive and constant during the period of analysis.

The multiple objective function can be divided into four parts $f(x_1, x_2, x_3) = F_1 + F_2 + F_3 + F_4$ as follow:

a) Net Equity:
$F_1 = x_1(M_C)^{-1}\left[(1+m_0)(1+m_1)(1+m_2)\right] - 1$

b) Investor's profitability:
$F_2 = (M_V)^{-1}\left[-3(1+x_2)^{\frac{1}{du}} + (Rp_0 + Rp_1 + Rp_2) - (1+i_b)^{\frac{x_3}{d_u}}\right] - 1$

c) Manager's profitability:
$F_3 = (M_L)^{-1}\left[x_1(1+x_2)^{\frac{1}{du}}(1+(1+m_1)(2+m_2)) - CT - IR - M_L\right]$

d) Risk assessment:
$F_4 = \alpha\sqrt{d_u}(M_R)^{-1}\left[x_1^{\frac{1}{2}}(1+x_2)^{\frac{1}{2d_u}}\left[1+(1+m_1)(2+m_2)\right]^{\frac{1}{2}}\right] - 1$

The related Hessian's Matrix is:

$$H_3 = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & 0 \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & 0 \\ 0 & 0 & \frac{\partial^2 f}{\partial x_3^2} \end{pmatrix}$$

$D_1 = \frac{\partial^2 f}{\partial x_1^2} = -\frac{1}{4}\alpha\sqrt{du}(M_R)^{-1}[x_1^{-\frac{3}{2}}(1+x_2)^{\frac{1}{2d_u}}\left[(1+(1+m_1)(2+m_2))\right]^{\frac{1}{2}}]$

As $x_1, x_2, \alpha, M_R, d_u, m_1$ e m_2 are positives, then $D1 < 0$.

Using Laplace:

$$D2 = \left[\frac{\partial^2 f}{\partial x_1^2} \times \frac{\partial^2 f}{\partial x_2^2} - \frac{\partial^2 f}{\partial x_1 \partial x_2} \times \frac{\partial^2 f}{\partial x_2 \partial x_1}\right]$$

$$D3 = \frac{\partial^2 f}{\partial x_3^2} \times \left[\frac{\partial^2 f}{\partial x_1^2} \times \frac{\partial^2 f}{\partial x_2^2} - \frac{\partial^2 f}{\partial x_1 \partial x_2} \times \frac{\partial^2 f}{\partial x_2 \partial x_1}\right]$$

x_1 and d_u are positives and bigger than the others, so, assuming:

$$\varphi_1 = \alpha\sqrt{d_u}(M_R)^{-1}; \varphi_2 = [(1+(1+m_1)(2+m_2))]^{\frac{1}{2}} \text{ and}$$
$$\varphi_3 = \Big[x_1^{\frac{1}{2}}(M_L)^{-1}(1+x_2)^{\frac{1-d_u}{d_u}}\left((M_L)^{-1}+\frac{1}{2}d_u\right)+$$
$$\frac{1}{4}(M_L)^{-1}(1+x_2)^{\frac{1-2d_u}{d_u}}+\frac{1}{8}\varphi_1\varphi_2 x_1^{-\frac{1}{2}}(1+x_2)^{\frac{1-2d_u}{d_u}}\Big]$$

Then:

$$\frac{\partial^2 f}{\partial x_1^2}\times\frac{\partial^2 f}{\partial x_2^2} = \frac{1}{4}\varphi_1\varphi_2\frac{1-d_u}{d_u^2}(1+x_2)^{\frac{3-4d_u}{2d_u}}x_1^{-\frac{3}{2}}$$
$$\left[3(M_V)^{-1} - x_1((M_L)^{-1}+1)\right]$$
$$\frac{\partial^2 f}{\partial x_1 x_2}\times\frac{\partial^2 f}{\partial x_2 x_1} = \varphi 1\varphi 2\frac{1}{du^2}(1+x_2)^{\frac{1-d_u}{d_u}}x_1^{-\frac{1}{2}}[\varphi_3]$$

As:

$$\left[3(M_V)^{-1} - x1((M_L)^{-1}+1)\right] < 0$$
$$\varphi_3 = \Big[x_1^{\frac{1}{2}}(M_L)^{-1}(1+x_2)^{\frac{1-d_u}{d_u}}\left((M_L)^{-1}+\frac{1}{2}d_u\right)$$
$$+\frac{1}{4}(M_L)^{-1}(1+x_2)^{\frac{1-2d_u}{d_u}}+\frac{1}{8}\varphi_1\varphi_2 x_1^{-\frac{1}{2}}(1+x_2)^{\frac{1-2d_u}{d_u}}\Big] > 0$$
$$\frac{\partial^2 f}{\partial x_1^2}\times\frac{\partial^2 f}{\partial x_2^2} < 0$$
$$\frac{\partial^2 f}{\partial x_1 x_2}\times\frac{\partial^2 f}{\partial x_2 x_1} > 0$$
$$\frac{\partial^2 f}{\partial x_1^2}\times\frac{\partial^2 f}{\partial x_2^2} - \frac{\partial^2 f}{\partial x_1 x_2}\times\frac{\partial^2 f}{\partial x_2 x_1} = D2 < 0$$
$$D3 = \left(-(M_R)^{-1}(du)^{-2}\ln^2(1+i_b)(1+i_b)^{\frac{x_3}{d_u}}\right)\times D2 \text{ or } a\times b$$

$a < 0$ and $b = D_2 < 0$, then $D_3 > 0$. As $D_1 < 0, D_2 < 0$ and $D_3 > 0$ the function is neither concave or convex. Results obtained by conventional methods such as non-linear programming can be only local optimal solutions, thus reinforcing the use of intelligent algorithms.