A GENETIC ALGORITHM BASED ON 2-TUPLES FOR THE NEW PRODUCT DEVELOPMENT PROBLEM

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Abstract. In more and more uncertain environments, the companies find that the satisfying the needs of the consumers is not a strategic option but a strategic necessity. This paper presents a new model based on 2-Tuple Genetic Algorithm technique to the voice of consumer management in the New Product Development problem. Also, an illustrative example is offered in order to facilitating the explanation of the model.

1. Introduction

The aim of this paper is to present a model making it possible to determine the technical characteristics that should be incorporated into a new product. This would be done by optimizing the information available about consumer preferences, so that their requirements are taken into consideration from the beginning of the process of New Product Development (NPD).

The justification for the need to set up a model such as the one proposed here lies in the fact that the economic environment in which firms operate is characterized by great dynamism, implying large changes in economic and market conditions, combined with ever-swifter technological advances. In such circumstances, businesses must adjust their range of products continually, modifying or discontinuing current items and launching new products. In this way, the development and introduction of new ranges becomes a key element in companies' survival and growth.

In this sense, it may be observed that the process of NPD commences with customer expectations and concludes with the appearance of a finished product. Hence, the core question is one of translating client expectations into specifications internal to the firm and of transmitting these faithfully to the various divisions of the business that are involved.

In fact, customer expectations, which are the starting point for the development cycle and process, may be distorted and delayed in reaching those who have to convert them into the concrete tasks that must be performed to achieve a finished product. Thus, complete transmission of the information associated with the product, its rapid circulation and collaboration without reserve by all the divisions of the firm that share a common goal at a given moment are factors that offer a measurement of the agility and capacity to react of the business under consideration.

The ideas put forward above clearly show the need for a business to have some mechanism that permits the transformation of requirements expressed by potential customers into a set of product characteristics constituting the best combination possible.

On these lines, the second section of the paper presents a model for NPD that attempts to bring together both perspectives, by analyzing what variables should be considered, both from an external viewpoint (customer statements) and from within the firm itself (the statements made by design staff). Such a model strives to overcome the two limitations present in traditional models that constitute the main focus of attention of this paper, to wit:

Firstly, the need to adopt mechanisms permitting operations with linguistic information. In concrete, we are chosen a 2-tuples linguistic representation [14], which makes the procedure for aggregating multi-texture linguistic information easier.

Secondly, the model for NPD, through trying to yoke together endogenous and exogenous information, causes the number of relevant variables to be very large and the possible interrelationships among them means that the total of possible combinations is of such a size as to render difficult its resolution in a reasonably short space of time. The search for solutions to this problem led to consideration of the likelihood that new search and optimization mechanisms, specifically heuristics based on nature, might offer a solution for problems of high combinatorial complexity. The choice was made to implement a Genetic Algorithm (GA), and a presentation of this is made in the thirty section of the paper.

Thereafter, in the fourth section the principal lines of operation of the model for NPD based on a 2-Tuples Genetic Algorithm (2-TGA) are defined. For illustrative purposes an example of a practical application is included in the fifth section, with the aim of facilitating comprehension of the structure and functioning of the model constructed. Finally, the principal conclusions arising from the study undertaken are set out in the sixth section.

2. New Products Development (NPD)

In an environment of changes in economic and technological conditions, together with an increased level of competition, both local and global, variations in consumer needs, the rapid obsolescence of products and the emergence of new markets, it is essential for firms to respond quickly in the development of new products ([4], [9], [13], [24]). In general, it is accepted that a rapid response to the market can yield a substantial gain in future market share, as reflected by the conclusions reached by a number of studies (among others, [25], [8], [5]).

In addition, the uncertainties present in markets and technology imply that such processes should be carried out in a flexible way, with the aim of minimizing the risks in the project, as any process of innovation brings with it an inherent market and technological risk [18]. The market risk derives from the degree of originality and complexity of conception of the new product, while the technological risk is determined by the degree of innovation in the technology used. In both cases this is from the viewpoint both of the market and of the firm itself. Both sorts of risk can provide an explanation for the high failure rates affecting the development of new products ([7], [10]).

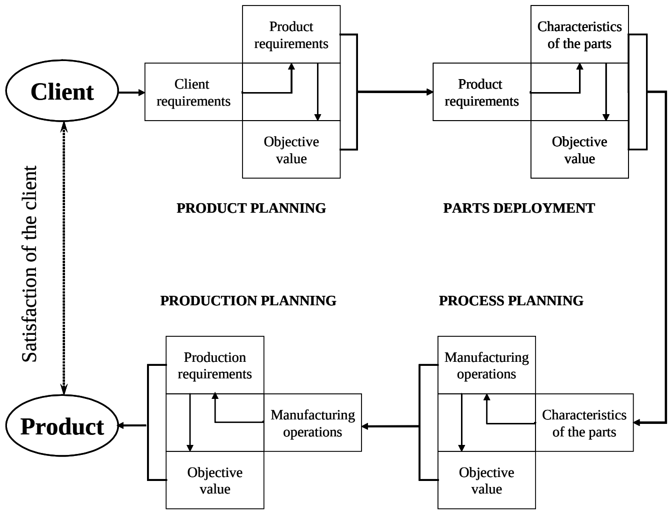

Fig. 1. New product development process

Moreover, the literature offers a range of studies attempting to identify the factors determining the success of new products in the market, so as to improve the efficiency of the process of new product development ([20], [21], [11], [17], [23]). Between the works that recognize that one of the main factors of success in the NPD consists of satisfying the needs of the consumers are [1], [3], [6] and [2]. Another factors for success is the way in which the process of NPD is carried out is of particular relevance, because, as Fig. 1 shows, it starts with consumer expectations and ends with the appearance of a finished product.

Thus, we need to translate consumers' expectations into specifications for use within the business and to transmit such specifications faithfully to the various divisions involved is not to be achieved without difficulty, as it commonly runs up against numerous obstacles, whether arising from the firm's structure, from its operational procedures or from the very nature of the development process. In its turn, the conversion of consumer requirements into fully detailed technical design specifications may be a hard task, since client needs are often fuzzy or vague, and in many cases contradictory. Indeed, as technical specifications for a product are expressed in a sort of language quite different from that used in stating consumer necessities, the voice of the client is frequently not heard fully clearly and the end result is a product that does not completely satisfy consumer requirements.

Thus, with the object of building a model that will permit determination of what combination of characteristics should be incorporated into NPD, the analysis to be carried out must first of all consider the variables affecting both potential technical features and requirements stated by clients. This will allow any possible relationships between these two types of information to be noted.

In this way, a list of the various requirements (requirements of consumers) put forward for the new product can be taken into consideration, such as:

$$RC_i \qquad i = 1,2,...,n$$

together with characteristics (characteristic aspects) that might be built into it:

$$CA_j \qquad j = 1,2,...,m$$

This initial information may then be reflected in a double-entry matrix in which any relationships (r_{ij}) between the variables can be specified, as follows:

$$\begin{array}{cc} & \begin{bmatrix} CA_1 & \dots & CA_j & \dots & CA_m \end{bmatrix} \\ \begin{bmatrix} RC_1 \\ \dots \\ RC_i \\ \dots \\ RC_n \end{bmatrix} & \begin{bmatrix} r_{11} & \dots & r_{1j} & \dots & r_{1m} \\ \dots & \dots & \dots & \dots & \dots \\ r_{i1} & \dots & r_{ij} & \dots & r_{im} \\ \dots & \dots & \dots & \dots & \dots \\ r_{n1} & \dots & r_{nj} & \dots & r_{nm} \end{bmatrix} \end{array}$$

In accordance with the above, the point of interest would lie in working out the combination of characteristics that would maximize the relationships shown, while optimizing the remainder of the information available, both on requirements (exogenous information) and on the product's own characteristics (endogenous information).

For the purposes of the model put forward in this paper, the exogenous information coming from outside the business is summed up in the following three variables:

- The importance of the requirements ("requirements of consumers, ponderated" RCP_i).
- Competitive evaluation or external benchmarking (ti).
- Correlation between requirements (γij).

The aspects which may affect the selection of possible characteristics for inclusion in the new product on the basis of information supplied from within the firm, which in the model being proposed would be captured by the following four variables:

- Importance of features ("characteristic aspects, ponderated" CAP_j).
- Competitive evaluation or internal benchmarking (B_j).
- Technical difficulty (C_j).
- The correlation between characteristics (δ_{ij}).

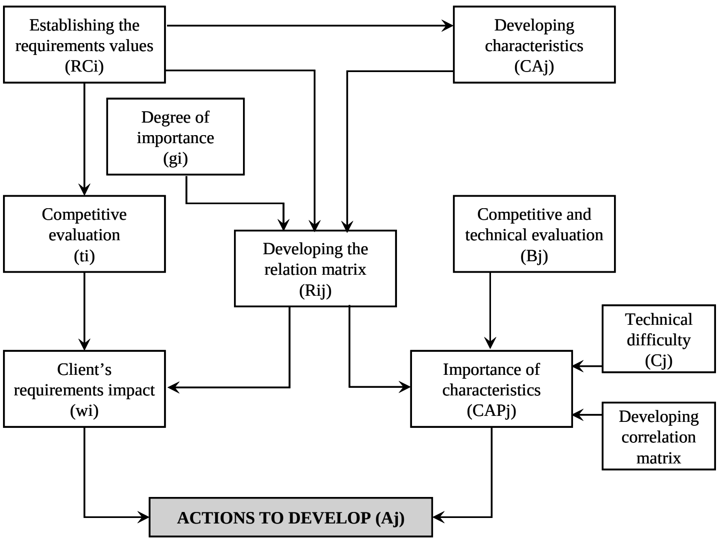

Fig. 2. The first phase of new product development

The considerations above make it appropriate to propose a flow chart as in Fig. 2, in which it is possible to visualize in an integrated and overall fashion the first phase of new product development. This is based on work by [19] which establishes the order in which different tasks and sections are performed so as to complete the production of a decision model.

3. Genetic Algorithms: General considerations

Genetic algorithms (GAs) are methods based on the genetic processes of living organisms and are used in resolving search and optimization problems [16]. GAs use a direct analogy with natural behaviour in which the individuals involved in a population compete among themselves so that those individuals with more success in surviving have a greater probability of generating a large number of descendants while the less well-adapted yield a smaller number of descendants. In this way, species evolve by achieving characteristics that are more and more suited to the environment in which they develop.

The natural behaviour translated into GAs is shown in the diagram that constitutes Fig. 3, where it may be observed that its operation presents the following phases:

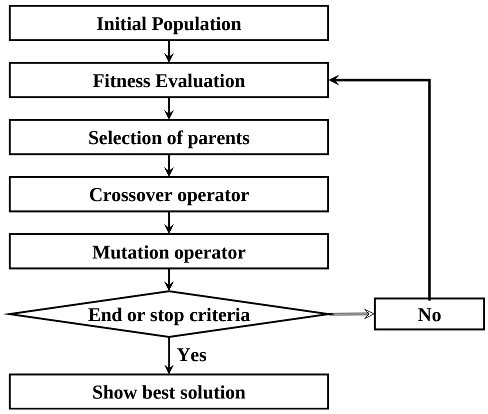

Fig. 3. Genetic Algorithms' Phases

The first step is to generate randomly a population of individuals each of which represents a feasible solution to the problem it is desired to solve. As a function of the goodness of the solution represented by each individual, the latter is assigned a value that defines the degree of effectiveness of that individual in competing for given resources. The greater the adaptation of an individual the higher the probability that it will be selected to reproduce and in consequence that its genetic material will be propagated in successive generations.

The process of reproduction is carried out by crossing the genetic material of the individual with that of another selected in the same way, generating a new population which replaces the previous one. This new population has the advantage of containing a higher proportion of good characteristics than the previous population.

Over successive generations the new populations will be better adapted than those from which they descend, simply by favouring crossings between individuals with better characteristics. This is because in such a fashion the most promising areas of the search universe are explored.

In addition it is possible to subject the population of individuals (solutions) to a process of mutation, with the intention of ensuring that no point in the search area has a zero probability of being examined.

The basic functional principles of GAs were put forward by [16], although they have been further developed by other authors (for instance, [12], [21]).

4. Development of a 2-tuples Genetic Algorithm for NPD

This section will attempt to describe the components of the sort of GA implemented as a mechanism for optimizing the information available to the decision process about the characteristics that should be emphasized in developing a new product.

Implementation of the GA was done with a view to operating with language information and to facilitating the adoption of decisions independently of the number of characteristics and requisites involved.

Further, the starting point was the assumption that to develop its new product, the firm has to hand a volume of resources established a priori, so that the optimum combination of characteristics will have to fit into such a budgetary restriction.

4.1. Codification of the solutions

The solution sought should establish a given number of characteristics implying a "good" combination, without their order being of any importance. For this reason a representation by means of vectors of whole numbers was chosen. The vector's length is equal to the number of characteristics possible (*m*) and each whole number thus represents the number of the characteristic that should be considered in reaching a decision.

As for the selection of the initial population, the option taken was for random initialization such that the same number of vectors of random whole numbers would be generated as there were individuals in the initial population. An example of the representation of a solution for the case of 10 possible characteristics might be $S = (10, 8, 1, 6, 5, 7, 9, 4, 3, 2)$.

However, as mentioned above, the combination of characteristics that can be achieved is limited by the costs to which they are subject, since it is a requisite that the characteristic should fall within the budgetary constraints. In consequence, the randomly generated solutions must be submitted to a procedure to eliminate individuals or solutions that are not feasible. The mechanism used for this consists of reducing the initial combination of characteristics to one whose cost does not exceed the established budget. For this purpose, the cost of each solution, starting with the first number in the vector representing them, is added to a running total, so that once a point is reached at which there would be a budget over-run, all further positions are taken as being zero. In this way, if the cost of each characteristic is as follows:

$$CA_1 = 10 \quad CA_2 = 8 \quad CA_3 = 5 \quad CA_4 = 2 \quad CA_5 = 12 \quad CA_6 = 7 \quad CA_7 = 12 \quad CA_8 = 3 \quad CA_9 = 10 \quad CA_{10} = 4$$

the conversion of the initial solution S into a feasible outcome for a budget fixed at 35 monetary units would yield a representation like the following: $S = (10, 8, 1, 6, 0, 0, 0, 0, 0, 0)$

This procedure must be repeated for each generation, since the action of the genetic operators can lead to changes in the position that a given characteristic occupies in the vector of whole numbers simulating the solution. This would alter the cost accumulated in vector order.

4.2. Fitness Function

As a measurement of the adequacy of each solution generated both in the initial population and as the genetic operators work on successive iterations, the proposal would be to utilize the fuzzy model described in the section. In this way, a fuzzy number ($\tilde{F}_S$) would be obtained, indicating the goodness of each solution. Comparison of the goodness of the various solutions obtained was done on the basis of the fuzzy distance, defined as follows:

$$d\left(\tilde{A}, \tilde{B}\right) = \int_{\alpha=0}^{1} \left(\left| A_\alpha^1 - B_\alpha^1 \right| + \left| A_\alpha^2 - B_\alpha^2 \right| \right) d\alpha$$

where $\left[A_\alpha^1, A_\alpha^2 \right]$ is the interval of confidence of $\tilde{A}$ for a level of presumption α.

4.3. Selection operator

The selection operator permits determination of which chromosomes in the initial population go on to have an active part in the reproductive process. In the model proposed a method of selection proportional to adequacy or roulette method [12] was used, setting down that those individuals with higher adequacy will have a greater likelihood of being selected as parents.

4.4. Crossover operator

In the GA proposed, the choice was made to utilize a variant of the classic crossing operator, which is the double point cross or crossing at two points. This process consists of choosing two points at random and dividing the chains representing the individuals selected as parents into three segments, a head, a central section and a tail, interchanging the central sections of the parent chains and obtaining two offspring that will have characteristics from both initial chains.

Nonetheless, in view of the coding mechanism used, this operator's action can lead to the repetition of certain characteristics in the descendents, because the parts of the parents exchanged may contain identical characteristics. Consequently, it is necessary to subject the individuals resulting from this operator to a procedure allowing the elimination of such repeats.

An example of the functioning of this operator might be as follows: Given parents $S_1 = (2, 3, 5, 1, 9, 10, 8, 7, 6, 4)$ and $S_2 = (1, 2, 6, 5, 10, 9, 4, 8, 3, 7)$, if the randomly selected points for crossing are points 2 and 6, the interchanging of the central chain of the two parents will yield the following descendants:

$$S_1 = (2, 3, 6, 5, 10, 9, 8, 7, 6, 4) \qquad S_2 = (1, 2, 5, 1, 9, 10, 4, 8, 3, 7)$$

It can be seen that the first offspring has a repeated characteristic 6 and missing characteristic 1, while the second offspring is lacking characteristic 6 and has a superfluous 1. In consequence, by simply interchanging these characteristics in the two resultant individuals, both would fall into conformity with the coding utilized, as shown below:

$$S_1 = (2, 3, 1, 5, 10, 9, 8, 7, 6, 4) \qquad S_2 = (1, 2, 5, 6, 9, 10, 4, 8, 3, 7)$$

In this way, after the crossing operator has been applied two new individuals representing solutions to the problem are obtained, although there is a need to run them once more through comparison with the budgetary restriction fixed a priori in order to ensure their feasibility.

4.5. Mutation operator

The purpose of this operator is to increase diversity in the set of solutions. In the model proposed mutation is performed on a random basis, combined with an interchange of characteristics. This means that a position in the chain is selected at random and a characteristic is likewise randomly chosen to move to occupying the given position in the chain. After this operation the characteristic is present in duplicate and the initial characteristic is missing, so that to avoid this flaw the place where the repeated characteristic is set in the chain is located and it is then changed for the missing one.

An example of the functioning of this operator is the following: $S_1 = (2, 3, 1, 5, 10, 9, 8, 7, 6, 4)$

If the place selected for the mutation to affect is the third position, and the characteristic randomly chosen is number 9, the new individual would in principle be represented as: $S_1 = (2, 3, 9, 5, 10, 9, 8, 7, 6, 4)$. The new characteristic occurs twice while the original characteristic (1) has disappeared from the representation of the solution. Thus, the position occupied by the repeated characteristic is located and it is replaced by 1: $S_1 = (2, 3, 9, 5, 10, 1, 8, 7, 6, 4)$. After this movement, the resulting individual must be subjected to the process for handling individuals that are not viable on the basis of the budget established.

4.6. Criteria for terminating or halting the search for the best solution

In choosing the criterion for bringing to a halt execution of the algorithm the route taken was to set a number of generations defined by the end user of the model as one of its operational parameters.

Further, with the aim of not losing any good solutions arising in each generation, the mechanism called "elitism" [12] was introduced. This consists of holding on to the best individual in a generation during following iterations until another individual betters it in adequacy for the problem. In this way, through elitism, it is possible to avoid loss of the best solution from a given generation until it is improved upon by another individual which will take its place as the elite, and keep this until an even better solution emerges.

5. Practical application of the model

With a view to facilitating detailed analysis of the functioning of the model put forward, the following example is considered: In order to develop a new product a list of the requirements mentioned by clients ($n = 15$) has been drawn up, as also the weighting that they assign to each. Likewise, an inventory is available of the possible technical characteristics ($m = 10$) that could be incorporated into the new product, seen from an internal perspective, and the relationships between these and the requirements mentioned ($\tilde{r}_{ij}$) worked out and set down in Table 1.

	$\tilde{g}_i$	CA_1	CA_2	CA_3	CA_4	CA_5	CA_6	CA_7	CA_8	CA_9	CA_{10}
RC_1	VI	VS		M							
RC_2	VI	S	QW	W							
RC_3	I	W	VS	QS	EW						
RC_4	M	E		VW							
RC_5	VI	VW	EW		VS	M	M				
RC_6	I				S	S	VW				
RC_7	OLI				QW	M	M	QW			
RC_8	OLI									M	
RC_9	VI							VS		W	
RC_{10}	M							QS	VW	QW	
RC_{11}	OLI										VW
RC_{12}	M							W	QW	VS	E
RC_{13}	I							M		VW	QS
RC_{14}	VI							M	M	S	S
RC_{15}	VI								E		M

Table 1. Relationships between requirements and characteristics

Where, as it is known

$\tilde{r}_{ij}$ = {EW, VW, QW, W, M, S, QS, VS, E}, with the follow semantic EW = Extremely_Weak, VW = Very_Weak, QW = Quite_Weak, W = Weak, M = Moderate, S = Strong, QS = Quite_Strong, VS = Very_Strong and E = Essential.

$\tilde{g}_i$ = {N, OLI, M, I, VI}, that is N = Nil, LI = Of_Little_Importance, M = Middling, I = Important and VI = Very_Important.

The values listed above permit an awareness both of the importance or weighting of requirements ($\widetilde{RCP}_i$) and of the importance or weighting of characteristics ($\widetilde{CAP}_j$).

In the example, after the unification and aggregation processes, the valuation for the importance of each requirement is obtained, as the Table 2 shows.

	RC_1	RC_2	RC_3	RC_4	RC_5	RC_6	RC_7	RC_8	RC_9	RC_{10}	RC_{11}	RC_{12}	RC_{13}	RC_{14}	RC_{15}
Ponderation	VI	VI	I	M	VI	I	OLI	OLI	VI	M	OLI	M	I	VI	VI
Value	QI	OLI	M	OLI	OLI	M	AU	AU	I	AU	N	OLI	M	I	QI
Simbolic Translation	-0’50	0’33	-0’25	-0’50	0’20	-0’33	0	0	0	0’33	0	0’25	-0’33	-0’50	0

Table 2.

established by means of the set of linguistic terms $\left\{s_0^9, s_1^9, s_2^9, s_3^9, s_4^9, s_5^9, s_6^9, s_7^9, s_8^9\right\}$ defined with the labels: Null, Almost_Null, Almost_Unimportant, Of_Little_Importance, Medium, Important, Quite_Important, Very_Important and Essential , respectively, that is {N, AN, AU, OLI, M, I, QI, VI, E}.

The obtained result provides the same evaluation for several requirements. Nevertheless, it is possible to discern among them by using the information of the symbolic translation variable, shown in the previous table.

Evaluation in comparison with competing products fixes a measurement for the firm's situation with regard to fulfilment of consumer requirements in the light of competition. The values utilized in the example of a practical application are shown in Table 3.

	RC_1	RC_2	RC_3	RC_4	RC_5	RC_6	RC_7	RC_8	RC_9	RC_{10}	RC_{11}	RC_{12}	RC_{13}	RC_{14}	RC_{15}
$\tilde{b}_i$	G	E	E	G	A	P	A	P	B	P	A	E	G	P	B
$\tilde{m}_i$	E	P	A	E	A	E	A	G	E	E	E	E	B	B	E

Table 3. Values for the valuation in comparison

Here: E = Excellent, G = Good, A = Acceptable, P = Poor and B = Bad.

The linguistic labels associated with the evaluation carried out on technical characteristics, both for the firm's current status and for products from the competition, are indicated in Table 5.

	CA_1	CA_2	CA_3	CA_4	CA_5	CA_6	CA_7	CA_8	CA_9	CA_{10}
$\tilde{b}_j$	E	G	G	B	A	G	G	P	E	G
$\tilde{m}_j$	E	P	A	E	G	E	G	A	B	P
$\tilde{C}_j$	VL	L	H	VH	M	H	H	L	VH	H

Table 4. Linguistic labels for the evaluation

In the Table above the values associated with the technical difficulty of each characteristic are also shown, with the labels used being the following: VL = Very_Low, L = Low, M = Medium, H = High and VH = Very_High, this is {VL, L, M, H, VH}.

The correlations existing both between the various requirements and between the possible characteristics are reflected in Table 5 and Table 6, respectively, with the meanings being as follows: Extremely_Negative, Very_Strongly_Negative, Strongly_Negative, Weakly_Negative, Practically_Zero, Weakly_Positive, Strongly_Positive, Very_Strongly_Positive and Extremely_Positive, that is {EN, VSN, SN, WN, PZ, WP, SP, VSP, EP}.

	RC_1	RC_2	RC_3	RC_4	RC_5	RC_6	RC_7	RC_8	RC_9	RC_{10}	RC_{11}	RC_{12}	RC_{13}	RC_{14}	RC_{15}

RC_1		EP						SP							VSP
RC_2	EP					WP	PZ					VSN			
RC_3															
RC_4						WN	PZ							VSP	
RC_5															
RC_6		WP		WN							EN				
RC_7		PZ		PZ											
RC_8	SP														WN
RC_9															
RC_{10}															
RC_{11}						EN									
RC_{12}		VSN													VSP
RC_{13}															
RC_{14}				VSP											
RC_{15}	VSP							WN				VSP			

Table 5. Correlations between requirements

	CA_1	CA_2	CA_3	CA_4	CA_5	CA_6	CA_7	CA_8	CA_9	CA_{10}
CA_1		EN						WP		SP
CA_2	EN					WP	VSN	VSP		
CA_3										
CA_4						EP	WP		WN	
CA_5										
CA_6		WP		EP						
CA_7		VSN		WP						
CA_8	WP	VSP								VSP
CA_9				WN						
CA_{10}	SP							VSP		

Table 6. Correlations between characteristics

The linguistic valuations of the variables are unified in the chosen dominion of expression *l(2,9)*, by using the function of transformation for 2-tuples representation ([14], [15]), so that it is possible to operate with this information.

As for the development cost for each characteristic, the values applied in the example of a practical solution are those listed below:

$CA_1 = (1000, 1100, 1200, 1300)$ $CA_6 = (1350, 1370, 1380, 1390)$
$CA_2 = (1300, 1340, 1350, 1350)$ $CA_7 = (1100, 1180, 1180, 1200)$
$CA_3 = (600, 600, 600, 600)$ $CA_8 = (90, 110, 120, 130)$
$CA_4 = (90, 95, 100, 104)$ $CA_9 = (850, 900, 900, 950)$
$CA_5 = (1420, 1430, 1440, 1450)$ $CA_{10} = (750, 760, 800, 850)$

Once the values in use for the example have been fixed it is necessary to establish the budgetary restrictions put in place by the firm in setting the maximum cost that can be afforded in the development of the new product. In this example a budgetary restriction ($\tilde{B}$) has been assumed such that:

$$\tilde{B} = (4400, 4500, 4500, 4600)$$

It is likewise necessary to define the operational parameters for the genetic algorithm, which for illustrative purposes were assumed to be as follows:

Number of generations: 50
Number of individuals: 100
Probability of crossing: 50%
Probability of mutation: 10%

The screen print shown in Fig. 4 indicates the evolution of the best individual in each generation.

In this screen it can be observed that the obtained solution presents the following combination of characteristics *S = {6, 4, 3, 9, 8 10}*, with a cost that will not be less than to 3,730 u.m., nor more than to 4,024 u.m., and between 3,835 and 3,900 u.m. being the most likely.

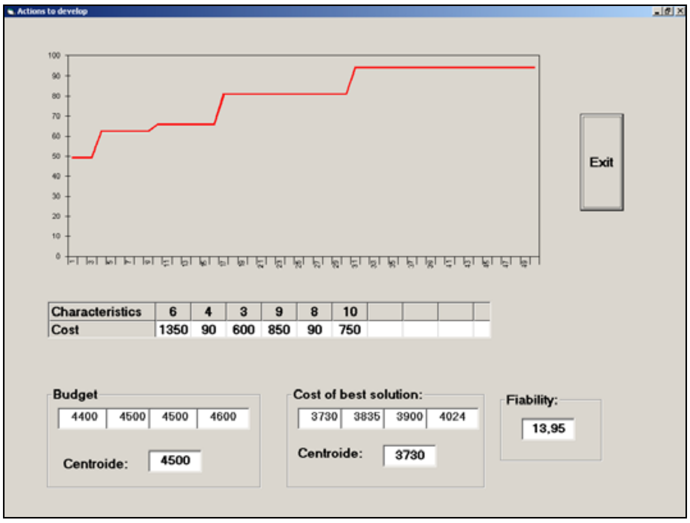

Fig. 4. Evolution best individual in each generation

6. Conclusions

The importance that the New Products Development has in the survival of the companies widely is recognized. In more and more uncertain environments, an increasing competence, mature industries, demanding markets and constant technological advances, the companies find that the satisfying the needs of the consumers is not a strategic option but a strategic necessity. In fact, one of topics of business management more important and greater complexity is the voice of consumer management in the development and introduction of new products.

This work show a new soft-computing based decision support system to help companies to cope with challenges of globalisation: contracting life cycles, high quality product, minimum time to market and flexibility to change. For this purpose, a 2-Tuples Genetic Algorithm model was built up as a means of optimizing linguistic information so as to permit solutions to be provided in environments of high combinatorial complexity.

In this fashion, once the principal defining aspects of the considerations laid out above had been presented, a model of 2-TGA was adumbrated whose application to NPD, supplemented with a complete illustrative example, permits it to be demonstrated that this model overcomes the drawbacks described earlier, making it easy for the decision process to be carried out with full account taken of the conditions of uncertainty and complexity that characterize current economic reality.

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