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Optimization of touristic distribution networks using genetic algorithms

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Abstract

The eight basic elements to design genetic algorithms (GA) are described and applied to solve a low demand distribution problem of passengers for a hub airport in Alicante and 30 touristic destinations in Northern Africa and Western Europe. The flexibility of GA and the possibility of creating mutually beneficial feed-back processes with human intelligence to solve complex problems as well as the difficulties in detecting erroneous codes embedded in the software are described. A new three-parent edge mapped recombination operator is used to solve the capacitated vehicle routing problem required for estimating associated costs with touristic distribution networks of low demand. GA proved to be very flexible especially in changing business environments and to solve decision-making problems involving ambiguous and sometimes contradictory constraints.

MSC: 90B20

Keywords: Distribution networks, vehicle routing problem, tourism demand, air transportation, genetic algorithms, edge mapped recombination operator

1 Introduction

Travel and tourism represent a total market which is of interest world-wide (Middleton, 1988). Regarding tourism, the transport of travellers to their destinations through the appropriate distribution channels constitutes one of the essential elements of competitiveness for the sector. Operational factors, infrastructure, equipment and

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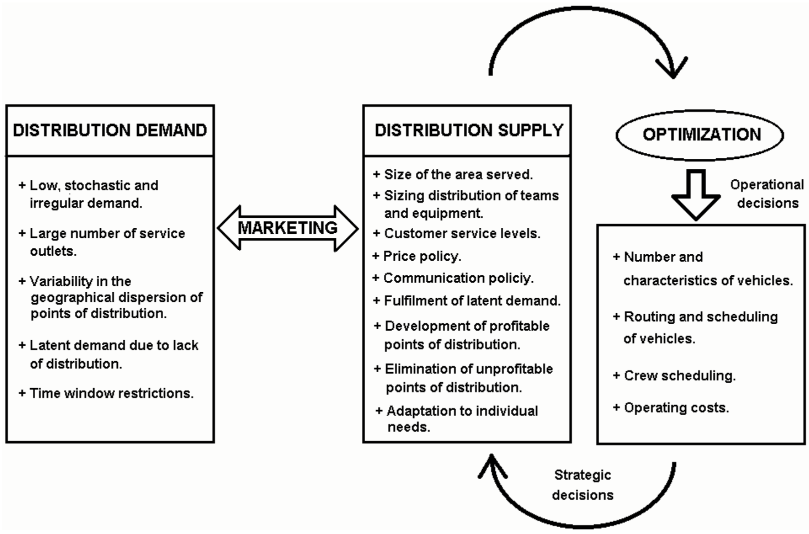

Figure 1: *Marketing and managing low demand distribution networks.*

government regulations are elements that affect the cost, speed and convenience with which a traveller may reach his destination. Therefore, operating costs are a primary input to pricing decisions. The decision-making problems associated with the management of touristic distribution networks of low demand require the use of efficient methods for routing optimization. Vehicle routing optimization at the operational level has a significant impact on both tactical and strategic levels, affecting cost estimation, optimum fleet size and optimum publicity policy. Figure 1 shows the variables to be taken into consideration for low demand distribution networks.

Many touristic services are sold in packages including round trip transportation from a fixed origin or hub airport to the corresponding touristic destinations; prices are fixed months before the transportation demand is known and last minute cancellations and new clients frequently change the demand estimations. When the number of passengers to be transported to each destination is low compared to the capacity of the optimum vehicle at the corresponding travel distance, the benefits or losses of the tour-operator are critically dependent on the optimization of the distribution system. Typically, the management of distribution networks implies the search for solutions which must fulfil a variety of objectives and constraints with a minimum use of resources; however, the number of possible solutions grows more than exponentially with the number of destinations and fleet size, and the optimal solution is not workable with exact optimization techniques because of the required computing time. The variety of objectives, resources and constraints that characterise actual management and transportation problems makes these problems inappropriate for conventional optimization techniques, which only search for the optimal solution in a deterministic way. In these circumstances, approximate methods of resolution as Genetic Algorithms

(GA), which emulate an efficient optimization strategy developed by Nature, do not attempt to find the optimal solution, but rather a reasonably good feasible solution depending on the computational effort. In the field of combinatory optimization and transportation problems, the term of metaheuristic is commonly used for these methods, while in other areas these methods are known as intelligent systems (Goonatilake *et al.*, 1995).

The management of low demand distribution networks, in which efficient vehicle routing is essential, generates decision-making problems with huge spaces of solutions. When the exact optimization techniques are not viable, heuristics, meta-heuristics, and probabilistic methods are reasonable alternatives. These methods do not guarantee finding the absolute optimal solution, but they do provide a limited search for feasible solutions, taking advantage of the particular characteristics of the problem under study, or taking advantage of the subjective human perception of what the characteristics of a good solution to the problem should be. Intelligent systems are appropriate for very complex optimization problems with multiple variables under a variety of constraints, including ambiguous and also contradictory objectives, such as those found in real-world problems. Goonatilake *et al.* (1996) described a number of methods for a variety of business and financial applications, from neural networks guiding direct mail campaigns to GA for credit assessment. Intelligent systems may also be used in data mining, transforming information into knowledge (Fayyad *et al.*, 1996). A case in point is the use of a feed-forward neural network pruned by simulated annealing for modelling runup and overtopping of rubblemound breakwaters (Medina, 1999). Yepes (2002) systematizes the set of methods of heuristic optimization and establishes the state of the technique regarding the used procedures in the solving of the Vehicle Routing Problem with Time Windows (VRPTW) and its extents.

Genetic Algorithms (GA) are meta-heuristic methods that usually serve as very flexible and robust tools for complex combinatorial optimization problems (Díaz *et al.*, 1996). In this paper, the general design procedure of a GA for optimization is described in reference to an example of GA originally developed to solve the classical Travelling Salesman Problem (TSP), but modified to solve the Capacitated Vehicle Routing Problem (CVRP). The practical lesson here is that a GA code can be adapted to solve increasingly complex problems with a minimum additional effort. In a dynamic business environment in which laws, rules, relationships and variables are constraints which change from day to day, it is imperative to have flexible and robust decision-making support tools which can easily change as quickly as the business environment does. There are a number of tourism studies in which these techniques are employed (see Canestrelli and Costa, 1991; Kottke, 1988; van der Knijff and Oosterhaven, 1990; Teodorovic, Kalic and Pavkovic, 1994; Brusco *et al.*, 1995, Hurley *et al.*, 1998; Medina and Yepes, 2000).

At the strategic level, an efficient tool to optimise vehicle routing problems is necessary to better estimate the travel and distribution costs associated with specific destinations and periods of low touristic demand. Offering a new touristic destination or eliminating an old one are decisions that require estimating the total economic impact. This in turn means taking into consideration the overall passenger distribution network. Strategic decisions require robust optimization methods which provide solutions related to the lowest possible transportation costs and the most reliable economic estimates.

At the tactical level, fleet size and characteristics of the vehicles must be decided on the basis of estimations of passenger transportation demand, distribution optimization and estimation of costs. Once the strategic decisions have been taken, affecting the structure of the distribution network, the optimization of fleet characteristics will favour to obtain the best results at the operational level.

At the operational level, routing and scheduling of vehicles must be adapted to a constantly changing non-deterministic passenger transportation demand. In this paper, an application at the operational level is provided considering a passenger distribution network with 30 touristic destinations in the Western Mediterranean area and Alicante (Spain) as the hub airport. Touristic demand is not deterministic and the CVRP is optimised using GA; the goal of these GA is to minimise the total transportation cost in a given scenario of low demand with a given stochastic structure. Therefore, GA serve not only as decision-making support tools at the operational level but at the tactic and strategic levels as well. Darwinian evolution emulated by GA is so intrinsically flexible and robust that it is hard to imagine a decision-making problem in which GA were not applicable; however, the practical problem here is to find efficient GA designs for each specific application.

2 Implementation of genetic algorithms

During the past decade, applications of a number of optimization techniques commonly used in artificial intelligence have been published in a variety of technical and scientific journals (Ansari and Hou, 1997). Evolutionary Programs (EP), Genetic Algorithms (GA), Neural Networks, Tabu Search, Simulated Annealing and Fuzzy Systems are some of the new techniques which have proved to be very effective in data mining and knowledge discovery (Fayyad *et al.*, 1996). They are also effective for solving complex optimization problems in a number of technical fields. GA emulate the natural evolution processes of complex living creatures. Populations of solutions form successive generations, in which survival and reproduction are probabilistically controlled by the best fitting criterion. The specific characteristic of GA is the efficient parallel exploration of the space of solutions based on the exploitation of good solutions induced by the crossover operators and the exploration of new solutions forced by the mutation operators. GA may run with single or several isolated populations or "islands" with a migration system; the size of the population may also differ from one application to another. The diversity not only increases with the size of the populations and the number of islands, but also with the computational cost. Additionally, GA are optimization techniques which may easily be adapted to run in co-operation with human intelligence because humans may provide specific sub-optimal solutions and GA have the ability to assimilate any solution during the evolution process. This characteristic may be crucial in finding feasible implementations of GA designed to replace decision-making tasks carried out by humans.

Typically, GA first define a specific letter or number code to represent any solution of the problem. Once the codification of the problems is defined, an initial population of solutions is randomly generated or created using any subjective or objective procedure. Then a cyclic process of selection, crossover and mutation changes the population in successive generations towards the optimum. If the diversity is too high, the evolution process may degenerate; on the contrary, if the population diversity is too low, the evolution process may stagnate in a local minimum and only a small proportion of the space of solutions are later explored during the computer time available.

There are several ways to implement GA for solving complex optimization problems (Davis, 1996), but the efficiency in a specific application depends exclusively on the GA design. This paper describes in detail an eight-step procedure, proposed by Medina (1998), which indicates the corresponding natural analogy and provides key ideas regarding the specific application to the CVRP example described in this paper.

1) Genetic architecture

Chromosomes made of strings of amino acids define the genotypes of living creatures. GA use chromosomes of strings of letters or numbers to define the characteristics of the solutions, named “individuals” in GA jargon. An explicit or implicit relationship between letters or numbers in the chromosome and the corresponding actual solution must be fixed in advance. Each possible solution must be related at least to one specific chromosome, which has to be attainable by crossover and mutation. Any possible chromosome obtainable by crossover and mutation must have the possibility of being decoded, and only one specific individual must be associated with a given chromosome. By analogy with natural evolution, the letters and numbers of the chromosome are named “genes”, and the alternative values of each gene are named “alleles”. A precise description of the genetic architecture and the possible alleles to each gene is required to run efficient GA; the effectiveness of the crossover operation is very sensitive to the selected genetic codification. In the study described in this paper, the airports are ordered and numbered, the chromosome of an individual is a string of numbers representing the successive airports to be visited, and the hub represents a new aeroplane to carry the passengers of the succeeding route. The length of the chromosome is equal to the number of airports plus the fleet size, and the alleles of each gene are the numbers of the airports. Figure 2 shows an illustrative example of a chromosome indicating a solution with two planes, one hub identified by 0 and nine airports identified by the corresponding numbers; the route of the first plane is {hub-1-2-3-5-4-hub} and the route of the second plane is {hub-6-7-9-8-hub}.

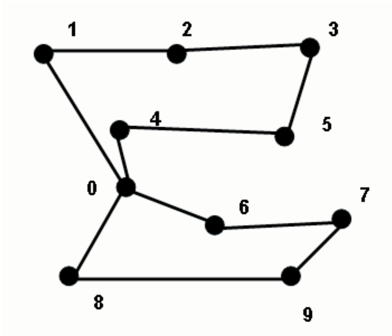

Figure 2: *Solution identified by chromosome {0-1-2-3-5-4-0-6-7-9-8-0}.*

2) Population size and population distribution

Natural populations of a given species are distributed in the space forming independent groups isolated from the rest of the species or groups connected by periodic migration movements. In the case of this research, the GA software is run with a personal computer with a single processor; evolutions with isolated populations with a number of individuals of five to ten times the number of destinations has given the best results. After generating the first independent evolutions in ten isolated islands, a sample of each one of the ten isolated final populations was taken to run the last evolution.

3) Initial population

The final result of the optimization process using GA is usually not sensitive to the fitness of the individuals in the initial population. Pure random alleles can be selected for each gene of each individual in the initial population; however, heuristics may help to improve the fitness of the initial population and reduce the time for convergence to the optimal solution. In the study described in this paper, radial order from the hub, minimum distance criteria between destinations and 2-opt branch exchange were used to form the individuals of the initial populations. Additionally, solutions created directly from human intelligence might be introduced in the intermediate isolated final populations to participate in the last evolution.

4) Evaluation and cost function

The natural selection tends to eliminate deterministically or probabilistically the individuals, which are not adapted to the environment or are less fit for the objective.

Given a specific individual and its environment, there is a cost associated to the individual. The environment (cost function) may or may not be stationary; in the case of the TSP, the cost associated to a solution is the total travel distance, the optimum being the one with the lowest cost. In the case of CVRP, the vehicles have a limited capacity and the demand of transportation may change on a daily basis. In a number of real-world problems, the environment is stochastic and non-stationary; in these cases, the solutions of the past may be used as members of the initial population of future evolutions in a different or a changing environment. Evaluation is critical for explaining the flexibility of GA because all the variables and constraints have to be reduced to the single variable "cost". Not only can objective variables such as "distance" or "time" be used to define the cost; but qualitative, ambiguous as well as subjective opinions may be used in the cost function to provide a better guide to the optimization process. For instance, an accident in a given airport or political turmoil can make it subjectively unpleasant for passengers to use routes which imply the use of specific airports during certain periods of time. In addition to the objective cost induced by "distance" and "time", it may be reasonable to include a subjective virtual cost associated with the use of specifically hard-to-deal airports. Experience can also help optimization because it may define virtual costs associated with subjective characteristics of the solution that will tend to favour solutions with the prescribed valuable characteristics. In the case which is analysed in this paper, the cost function takes into consideration the objective economic costs associated with travel distance and time of each vehicle of the fleet, but also includes virtual costs associated to violation of constrains as maximum capacity, maximum duration of the route, maximum number of flights for each crew in a route, etc. Legal and social constraints as well as quality of service must be transformed in virtual costs to properly guide the optimization process to a satisfactory solution.

5) Selection

Emulating natural selection, the individuals with lower costs in a given population have higher survival and reproduction rates. The worst individuals have to be deterministically or probabilistically eliminated; the probability of elimination may be proportional to the cost, proportional to the order, etc. The GA employed for this study uses a probability of survival inversely proportional to the order of the individual in the population, having the best individual two times the probability of survival than the second best, three times the third, etc. With these probabilistic criteria of survival, the individuals are randomly selected from a given generation to produce the offspring of the following generation. Additionally, the method included some degree of elitism because a very small probability of selection is always given to the absolute champion, although the absolute best individual found during the evolution does not belong to the current generation.

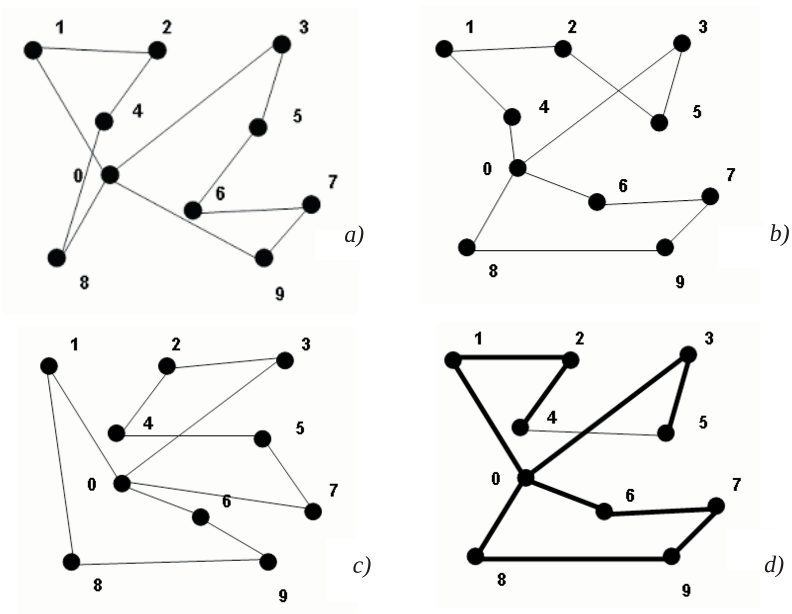

Figure 3: *Three parents edge mapped recombination operator generates offspring (d) based on parents (a), (b) and (c).*

6) Crossover

The crossover operation must exploit the good solutions transferring and spreading the desired characteristics of the best individuals from one generation to the next. The crossover operators read the genetic information of the selected individuals (parents) of a generation to produce viable individuals for the following generation (offspring). There are usually two parents who must have different genes. The crossover operator must not only ensure that the offspring are different from their parents, but that they also have some of their parents’ characteristics. One of the crossover operators used in this study is the classical one-point crossover operator which reads the genetic code of two selected parents, cuts the genetic chain in the same point, interchanges the chain tails, and changes genes to make viable offspring. A second crossover operator of the family edge mapped recombination operator described by Whitley *et al.* (1996) is also used in this study; this new operator is a generalisation of the edge mapped recombination operator considering three or more parents to produce one single offspring. The best performance has been obtained only with three parents; the offspring is formed by taking the routes that are present in the two or the three parents and completing feasible routings using the minimum distance criterion to form the offspring. Figure 3 shows the offspring obtained from three parents using the three parent edge mapped recombination operator.

The offspring have the arcs that are presents in two or three of the three parents; if three arcs are connected in a specific node, one of the three is randomly eliminated. Finally, the full offspring chromosome is obtained connecting the rest of the nodes randomly. Arc {0-3} belongs to offspring (d) represented in Figure 3 because it is part of the routes of the three parents; arcs {7-9}, {3-5}, and others belong to offspring (d) because they are part of the routes of the parents (a) and (b); arcs {0-1} and {2-4} belong to offspring (d) because they are part of the routes of the parents (a) and (c); arc {8-9} belongs to offspring (d) because it is part of the routes of the parents (b) and (c). No node in the offspring has three arcs and only the connection of nodes 4 and 5 is necessary to complete the chromosome of the offspring.

7) Mutation

The mutation has to explore the space of solutions providing the desired diversity in the population. The mutation operators change the alleles in a genetic code randomly, usually generating poor solutions that are eliminated in the successive selection processes. However, sometimes the mutation is beneficial to the solution and the new characteristic is rapidly spread in the population by selection and crossover. The GA used in this paper have seen different mutation operators designed to solve the specific local problems of routing: (1) exchange of one pair of random genes in the chromosome, (2) exchange of two pairs of random genes in the chromosome, (3) exchange of two random strings of genes of random length in the chromosome, (4) cut the chromosome and exchange first and second part, (5) change the order of a random string of genes of random length, (6) exchange two consecutive strings of genes of random length, and (7) select a string of genes of random length and put it in the first position of the chromosome shifting the corresponding genes.

8) Probability of crossover and mutation

According to Mitchell (1996), efficient crossover rates fall in the range of 75% to 95%, while bit mutation rates must be in the range of 0.1% to 1% to be effective. However, she indicated that for most applications crossover and mutation rates should not be constant, but should change during the evolution process to maintain a balance between exploration and exploitation of solutions. Julstrom (1995) proposed a dynamic assignment of probabilities for the different operators depending on the improvement obtained during the evolution process. In this study, the crossover operators have initial rates of 5% and 15% respectively, and the initial mutation rates are in the range of 5% to 20%. However, if no improvement is detected after a fixed number of generations, the probability rates assigned to each operator change following a first order auto-regressive process which is activated when stagnation is detected.

3 Application of genetic algorithms to routing problems

The GA described in this paper has been implemented in Visual BASIC to be used in a personal computer. In its present form, a homogeneous fleet is considered with the following input variables: (1) latitude and longitude of the hub and the destination airports, (2) mean velocity and maximum capacity of the aeroplane, (3) take-off, landing and taxi time plus mean airport delays, (4) costs associated with aeroplanes, crews, passengers and travel distance, and (5) the number of passengers to be transported to and picked up from each destination to the hub airport. Before using the GA software to solve transportation problems in different scenarios, it is first necessary to run several typical cases in order to check the different parameters controlling the evolution, such as the probabilities of crossover and mutation, the population size, the number of islands and the number of generations. The diversity in the population during evolution has to be studied in order to avoid both premature stagnation and degenerative processes. Once the parameters of the genetic program are fixed, GA are ready to solve efficiently the transportation problem associated with the simulated scenarios representing the unknown future, calculating costs of different alternatives.

A specific GA implementation requires making dozens of decisions about structure and parameters of the algorithm. There are millions of alternative GA implementations of a given problem and the efficiency of a specific GA implementation is highly nonlinearly dependent on the selected parameters; therefore, human intelligence is required to define reasonable structural parameters, crossover and mutation rates, etc. The results may differ with different GA parameters (i.e. crossover and mutation rates, etc.) but the intrinsic robustness of GA makes it easy to find a reasonably good implementation after some exploratory work. Nevertheless, it is not possible to be sure that a specific GA implementation of a given problem cannot be significantly improved by changing the GA parameters. For this reason, the GA algorithm employed in this research uses a dynamic assignment of crossover and mutation rates.

For a given problem, the possible comparisons of the quality of solutions using GA and other intelligent systems (i.e. Simulated Annealing, Neural Networks, Tabu Search, etc.) are inconclusive (see Yepes, 2002). Only specific computer codes can be compared and the specific implementations of intelligent systems depend critically on the author's competence in designing the algorithms and detecting erroneous code. For a given problem, the comparisons with simple heuristics are also inconclusive. The popular heuristics (i.e. nearest neighbour procedure and 2-opt branch exchange) are efficient for solving simple problems (i.e. TSP) with simple cost function variables (i.e. minimum total distance). For more realistic problems (i.e. CVRP) with complex cost functions variables (i.e. total distance, total time, number of aeroplanes, service interruption cost, maximum route time, etc.), the popular heuristics are not efficient.

GA may easily interact with human intelligence in solving the problems because humans may include solutions during the evolutionary process. The evolution may then "learn" from the human skills for optimization, and once a different solution is obtained, humans may also learn from how the machine successfully changed the human solution to find a better solution. This mutually beneficial response may be crucial for the final success in using GA as a decision-maker support system of a company.

Although GA are indeed extremely flexible and robust methods for solving complex optimization problems, it is necessary to warn the readers of the difficulty in checking the software code. Because of the intrinsic robust performance of GA, it is relatively easy to write an erroneous code, which may become embedded in the main code, being almost impossible to detect. The difficulty in detecting errors lies in the fact that neither the optimum solution nor a reasonable pace of progression of the evolutionary process is known in advance. If the basic evolutionary code is well written, it may give apparently good solutions although a certain erroneous code reduced significantly the effectiveness of the algorithm. The software could be checked using known optimal solutions of small size problems, but the result could never prove the absence of erroneous code, because the robustness of GA frequently allows one to find the optimal solution of small size problems. When an erroneous code is detected and corrected, the GA is more efficient and able to solve larger problems to the optimal point. Therefore, an undetected erroneous code should always be considered as a probability included in any GA code; it can always be generated by accident and sometimes it may also be generated intentionally when a team works together to write the code.

4 Application of genetic algorithms to optimize a low demand air transportation problem

For illustrative purposes, an application of GA is given below to analyze and optimize a low demand air transportation problem. The problem can be described by four factors: (a) the low demand distribution problem, (b) the model of transportation demand, (c) the fleet and transportation constraints and (d) the optimization and results.

a) The low demand distribution problem

In this study, we use the CVRP version to solve the operational problem which affects a tour-operator based in Alicante (Spain) specialised in non-massive touristic destinations in the Western Mediterranean area. When prices must be fixed in advance and demand is low and non-deterministic, it is of critical importance to use a flexible and robust optimization technique to minimise the transportation cost and to estimate mean costs in different scenarios. An estimation of the demand is known in advance, but a significant random component due to last-minute cancellations is always present.

b) The model of transportation demand

In this study, a stationary lognormal pdf (probability density function) and a double-variable first-order autoregressive stochastic structure are used to model the demand of transportation from the hub to each destination and from each destination to the hub. This model resembles the wave climate simulator proposed by Medina *et al.* (1991) for simulating time series of significant waves and periods in the Pacific Ocean. If demands follow the lognormal pdf, the normalised time series may be defined as:

$$x(i,n) = \frac{(\log[q_1(i,n)]) - Q_0(i)}{SQ_0(i)} \tag{1a}$$

$$y(i,n) = \frac{(\log[q_2(i,n)]) - Q_0(i)}{SQ_0(i)} \tag{1b}$$

in which $q_1(i,n)$ is the transportation demand during the day n from the hub airport to destination i,and $q_2(i,n)$ is the transportation demand from destination $i$to hub. $Q_0(i)$ and $SQ_0(i)$ are the parameters of the lognormal pdf. In this study, $Q_0(i)$=2.5 and $SQ_0(i)$=0.4 for all destinations; the average transportation demand is about 13 passengers with a coefficient of variation of 43%. The stochastic structure is given by

$$x(i,n) = A\,x(i,n-1) + \sqrt{(1-A^2)}\,w(i,n); \quad n = 1,2,3,\ldots \tag{2}$$

$$y(i,n) = B\,x(i,n-\delta) + \sqrt{(1-B^2)}\,v(i,n); \quad n = 1,2,3,\ldots \tag{3}$$

in which $x(i,n)$and $\mathrm{y}(i,n)$ are the normalised time series; $w(i,n)$and $\mathrm{v}(i,n)$ are independent white noises; A and B are the correlation parameters; and δ is the time lag parameter. In this paper, A=0.50, B=0.95 and δ =7.

c) The fleet and transportation constraints

The aeroplanes have a maximum capacity of 50 seats, a range of 2,250 km, and a travel speed of 240 knots. Each aeroplane departs from the hub airport with the passengers corresponding to the destinations in its prescribed route and has to deliver them to the destination, taking all the passengers in the route that have to return to the hub airport the same day. The number of planes to address the transportation demand and the total distance and flight time has to be minimum, without exceeding the capacity of the aeroplane and a maximum routing time of 10 hours. In the example given in this paper, the hub airport is Alicante (Spain) and the 30 destinations are: Ajaccio, Brest, Burdeos, Cannes, Cardiff, Dublin, Tangier, Casablanca, Tunis, Malta, Cagliari, Genoa, Palermo, Venezia, Lisbon, Oporto, Girona, Vitoria, Santander, Oviedo, Santiago de Compostela, Pamplona, Zaragoza, Granada, Jerez, San Sebastian, Reus, Mallorca, Menorca and Ibiza. The region of Alicante (Spain) has more than 53,000 hotel rooms and a theme park for mor than 2 million visitors (AVT, 2001).

d) The optimization and results

The GA optimization of passenger distribution at the operational level affects the decision-making process at both the tactical and strategic level. On the one hand, the effectiveness of GA affects the fleet size and prices to be charged; on the other hand, the sensitivity analysis for increasing or reducing demand of specific destinations may guide the publicity policy and the suppression or addition of new destinations (see Figure 1). The demand simulator described by Equations 1 to 3 provides the scenario in which the GA operate providing the best transportation solution each day. The service levels are considered in the routing optimization process by the maximum routing time and the economic extra-cost due to service interruption (over-booking). Figure 4 shows a typical graphic output for the CVRP defined above. Unit prices, aeroplane characteristics and travel conditions may be easily modified to affect only the cost function. Additionally, a graphic interface allows for the introduction of man-made solutions in the evolution process of GA. The cost function used in this example includes the following factors (rates): aeroplane travel distance (3 euro/mile), number of vehicles (3,000 euro/aeroplane), number of crews (1,800 euro/crew), optimal and maximum route time (6 and 9 hours), optimal and maximum load (45 and 50 passengers), mean aeroplane speed (240 knots), and service breakage (6,000 euro/time or load failure). In addition to the actual costs used to calculate the results given in Table 1, the cost function has virtual costs associated to non-optimal time and load solutions that guide the optimization problem to optimal solutions.

Table 1: *Estimated daily mean value and coefficient of variation of the most significant transportation load and cost variables.*

Variable	Daily mean	Coefficient of variation
Number of passengers from and to each destination	13	43%
Total number of passengers transported	800	6.1%
Number of passengers per kilometre to the hub	605,000	6.4%
Occupation of seats in aeroplanes (%)	65	4.2%
Cost of passenger transported from or to hub (EUR)	118	2.7%

Although the low demand is not known in advance, the fleet and the crews are known in advance. In the example, 4 aeroplanes and 15 crews are considered to satisfy the demand. Because transportation supply is stable, but transportation demand has a significant random component (i.e. last-minute cancellations), transportation load,

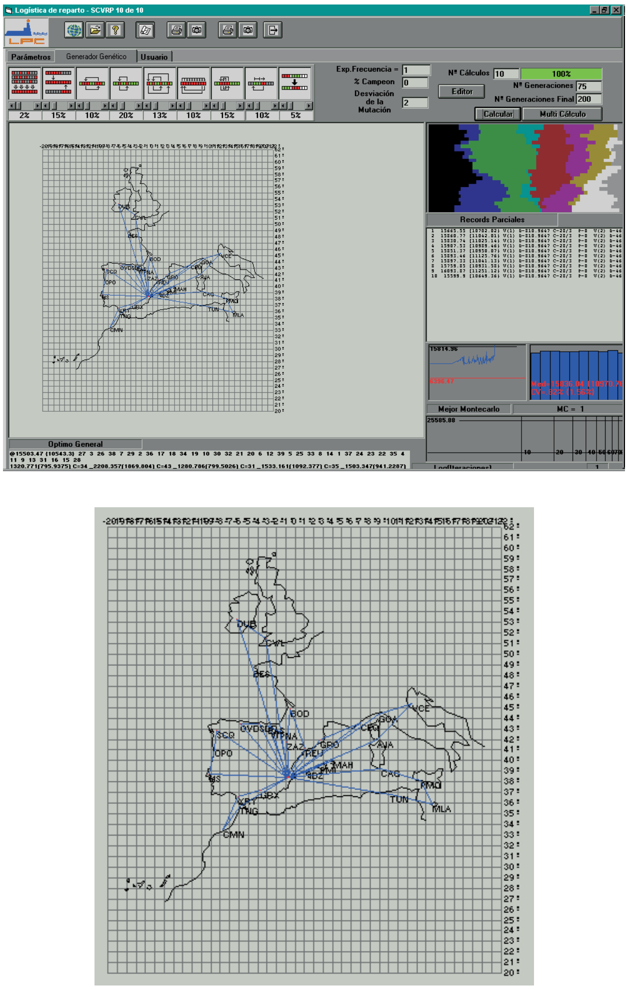

Figure 4: *Typical graphic output for the CVRP.*

optimal routes and profitability change daily. A simulation of thirty days with the parameters given above was generated and the corresponding GA optimised solutions were obtained. In this simulation, the mean travel time was 3.0 hours for passengers and 5.8 hours for crews. The daily mean values and coefficient of variations of the most significant transportation load and cost variables are given in Table 1. A sharp reduction of variability from the isolated and disperse transportation demand (CV=43%) to the cost of transported passenger (CV= 2.7%) is obtained everyday by the method of routing optimization using GA. The mean occupation of seats in the aeroplanes was 65%. The heuristics of nearest neighbour procedure and 2-opt branch exchange is almost as efficient as GA minimising total distances, but it is highly inefficient optimising more realistic multi-objective problems such as the CVRP described in this paper. However, efficient heuristics for TSP may be used to create the initial population of the GA, reducing the computational effort to find the optimal solution of the transportation problem.

5 Conclusions

GA are inspired in Darwinian natural evolution and provide very flexible and robust optimization techniques which are being applied in a wide range of scientific and technical fields. GA may be designed to work in co-operation with human intelligence in solving optimization problems, generating a mutually beneficial feedback process that might be essential in supporting or replacing human decision-making systems. The flexibility of GA allows for operations in changing business environments including the consideration of subjective, ambiguous and sometimes contradictory constraints. The intrinsic robustness of the optimization methods based on GA makes them very attractive for a variety of applications; however, robustness is also responsible when erroneous codes are accidentally embedded in the GA software which is usually very difficult to detect.

Although it is hard to imagine a decision-making problem in which GA were not applicable, efficient results require adequate GA designed for each specific application. Eight basic elements to design GA for general purposes are described in detail, pointing out the parallelism with natural evolution while a specific application to a given touristic distribution problem is analysed. The genetic architecture, the cost function and the crossover operators are the key elements for a successful implementation of GA for most specific applications. The GA employed in this paper use a new three-parent edge mapped recombination operator which was found to be very efficient. A genetic architecture and cost function easily changed the problem typology from the classic TSP to CVRP. The flexibility and capability to adapt to changing environments are indeed the strong points of GA.

GA are applied to solve a passenger distribution CVRP at the operational level with the hub airport in Alicante (Spain) and 30 touristic destinations in the Western Mediterranean area. The low touristic demand is modelled as a stationary lognormal with a double-variable first-order autoregressive stochastic structure. GA optimise the distribution of passengers day by day generating a precise description of the transportation scenarios and the costs associated with them. In the simulations, the coefficient of variations of both the cost of transported passenger and the cost of transported passengers per kilometre to hub were significantly lower than the coefficient of variations of transported passengers and transported passenger per kilometre to hub. The optimization method used as cost estimator affects the decision-making process both at tactical and strategic levels.

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Resum

Es descriuen els vuit elements bàsics per al disseny d'algoritmes genètics (AG), i s'apliquen a la resolució d'un problema de distribució de passatgers de baixa demanda amb un exemple centrat a l'aeroport d'Alacant i 30 destinacions turístiques del Nord d'Àfrica i l'Oest d'Europa. Es descriu tant la flexibilitat dels AG com la possibilitat de crear processos de retroalimentació amb la intel·ligència humana mútuament beneficiosos per a la resolució de problemes complexos, així com la dificultat d'identificar codis erronis en la programació. S'usa un nou operador de recombinació d'arcs de tres pares per resoldre el problema de rutes i vehicles amb restricció de capacitat, necessari per estimar els costos associats a les xarxes de distribució turística de baixa demanda. Els AG han demostrat una gran flexibilitat, especialment en entorns d'empresa canviants i en la solució de problemes de presa de decisions que involucren restriccions que són ambigües i, de vegades, contradictòries.

MSC: 90B20

Paraules clau: Xarxes de distribució, problema de rutes i vehicles, demanda turística, transport aeri, algoritmes genètics, operador de recombinació d'arcs