9

Mature Tourist Destination: A New Tool to Forecast Internal Composition of Its Demand

Montserrat Hernández-López
University of La Laguna, Tenerife, Canary Islands
Spain

1. Introduction

Tourism activity and its impact on the development and growth of specific economies are undeniable. Although tourism in its origins was considered as a luxury event only enjoyed by the very few, it now has not only been established as an inalienable right for every human being and recognized in the Universal Declaration of Human Rights (1948), but has also found a place in the household budget. The economic analysis of tourism is relatively recent and a review of the literature confirms the imbalance with regard to their different dimensions of tourism economics. Supply in general, specific tourist subsectors and the relationship between the public sector and tourism have received less attention in theoretical and empirical analysis. Demand, expense, forecast and impact multipliers of tourism, however, are areas that continue to be heavily studied. This chapter can now be added to the list of demand studies because it will show how tourist demand forecast can be carried out with a micro focus. This focus is essential in specific tourist destinations.

It is important to distinguish between new and mature tourist destinations. New destinations are beneficiaries of annual forecasts on tourist expense, number of visitors, number of nightly stays carried out with the help of available statistical-econometric techniques. However, in mature tourist destinations, where tourist demand is consolidated, another type of forecast is absolutely necessary. It is not aggregate, but instead directed towards the internal composition of the demand, that is, individual characteristics from future potential tourists. In this new approach the integrating elements of the tourist supply can be better adjusted to the specific characteristics of those tourists using that supplied service, with the consequential increase in the degree of satisfaction obtained by the tourist.

Nevertheless, this type of analysis, necessary from a private initiative perspective or a legislative and zoning point of view, must cope with its inherent limitations. On the one hand, the researcher usually must deal with the absence of empirical microeconomic data with a certain degree of depth or detail. Available individual information is usually limited to those that have carried personal interviews to tourists just before returning to their permanent residence, usually performed by official government organisms. But these interviews have just one aim: to obtain average values that synthesize all of the information on tourist expense, type of lodging and number of night stays, among others. Hence, in the majority of cases there is only access to summarized information by tourist groups, which necessarily leads to the type of typical aggregate analyses on different identifiable variables of tourist demand. On the other hand, there is an absence of appropriate statistical techniques to aid in the tourist forecast based on individual interviews. These interviews provide information on the changes in the demand composition for a specific destination. Fortunately the development of techniques in the fields of Computational Intelligence and Artificial Intelligence open up new research perspectives. Specifically, genetic algorithms, one such technique in Computational Intelligence, can serve as an appropriate tool in the analysis of the evolution of the characteristics of the potential clients of those tourist services that are offered in a specific destination.

The aim of this chapter is to show that the genetic algorithms can be conveniently adapted in its structure and in its component definitions when performing detailed forecasts on the tourist demand composition which are necessary in a mature tourist destination.

2. Tourist consolidation: The need to stabilize the number of satisfied visitors with the supply

Tourist activity generates a multiplier effect on the service sector and other sectors in an economy, and this resultant activity in turn drives and diversifies total economic activity. Tourism is frequently an important source of exports for an area, although the goods are not physically exported. Tourists travel to a country to participate in tourist services and the resultant paid currencies make up, in terms of balance of payments, an export of services similar to other goods and services. The export of the tourism sector becomes a source of income and employment for the population that is directly linked to tourism, but it also has an indirect impact on other sectors of the economy that are responsible for providing other produced goods and services in the region. From a strictly economic point of view, in the initial stage of tourism development, tourists expect that their arrival, together with an entrance of foreign currency, to be rapidly redirected to the production or import of those goods and services that are needed by the new visitors. In addition, the entry of foreign currency can be transformed into a source of regional financing for currently needed investments that are required in this non-existent tourist supply —namely lodging, transport, restoration.

In the economic take-off stage, the injection of capital provides an increase in residential income in the tourist area —more jobs, opening or reactivation of business activities—, which translates directly in purchases, taxes on tourist goods and services and income from rentals and lodging, or what is the same, the entrance of foreign currency. On the other hand, the increase in residential salary income can simultaneously convert these residents into tourists in other areas. This transformation, in turn, when added to the needed imports to satisfy tourist demand, non-resident salaries, lost income due to exchange rate in tourist operation transactions paid in the country of origin, tourist promotions carried out in the foreign countries, the expenses in infrastructure improvements, and investments in tourist activities, cause foreign currency exiting.

The result from the consolidated stage of tourism —or the presence of a mature tourist destination— is therefore a set of related effects amongst themselves which are concerned with the degree of dependence of the destination with respect to the exterior, its own tourist development strategy, production, employment, balance of payments, exchange rates, monetary supply, public income and expenses, inflation, property value speculation, income distribution, consumption habits, professional training, socio–cultural changes, effects on the environment, rural settings and regional development. Bull (1992) reviews the externalities generated by tourism and classifies them from the individual and group perspective. The externalities for individuals are divided into 1) benefits: new transport route connections, new shops and amenities, high property values, evidence of local positive effects (mirage effects); 2) costs: inflation, traffic congestion, noise. Externalities for governments and groups: 1) benefits: tax revenue increases, increase in cultural value, preservation of flora and fauna; 2) costs: maintenance of tourist infrastructure where tourists do not cover these expenses, additional services —police, healthcare—, destruction of flora and fauna.

Opportunity costs must be considered and understood for each one of the actions that it causes before the proliferation and potential reach of tourism expansion. Opportunity costs reflect the value that is given up by using resources in the tourist activity and not in other activities. Nevertheless, all of the transformations and mechanisms that are put into place and that are interrelated with regards to the numerous arrivals of visitors to the area complicate the measure of what really generates tourist activity. The inherent difficulties found in the nature of the service industry and actual circumstances may, however, reflect that the costs are not always valued as highly as the benefits.

This fact could be reduced in part if some reliable statistics were available on tourism supply and demand components. Nevertheless, available statistics provide a very limited view of the reality hidden behind this market. A common calculation, especially in areas that have been intentionally developed as tourist destinations, includes figures that are given which evaluate the number of expected foreigner visitors that they will periodically receive. The continuous increase of such a number continues as if it were the only sign of the tourist destination. Nevertheless, as Frechtling stated (1987a, 1987b), in a world of limited resources, the measure of economic profits from tourism in an area without parallel measure of the associated costs of the same, can induce, not only harm to the environment, but also waste public funds or drastically reduce the quality of life of the local residents.

Nevertheless, it is necessary to understand the difficulty of establishing a real value of these impacts —positive and negative—, created in most cases from mass tourism, as analyzed by Archer & Cooper (1998), and how these impacts can be transformed spectacularly by the appearance and the quality of the receiving area and the lifestyle of the residents. In spite of all of the inconveniences that could exist in the valuation of this subsector, the transcendence of tourism as an activity with multiplier effects, extremely complicated in terms of control from the supply perspective, and only quantifiable from the demand perspective, is such that all generalizations that are carried out will still be useful.

In summary, tourism interacts with general economic activity of the receiving area, impacts economic growth of the surroundings where the activity is developed and is influenced by it. These interactions should not be ignored by any tourism planning project, and the project will benefit if in the initial stages of tourism take off is accompanied by good forecasts of the aggregate tourist demand, and, in the case of a mature destination, other types of disaggregate forecasts on the potential tourist of the destination will be available.

3. Aggregate and disaggregate focus on tourist demand

A tourist market is considered established when a potential tourist and a tourist supplier contact each other. Tourism supply tries to adapt its offer to the particularities of the potential tourist, and if these are disregarded or unknown, the existing imbalance between both sides of the tourist market of the developed model will cease to exist in the tourist destination. In this case, Say´s Law does not seem to apply, instead demand determines the guidelines of how supply will act. It is clear that additional encouragement in the path towards knowledge of future demand at a specific site is welcome, not only in absolute terms —aggregate tourist demand—, but also in internal composition —disaggregate demand.

Although there is a need by the supplier to know the individual peculiarities of potential tourists, the arrival of an important number of tourists to specific countries or areas in a tourist destination has drawn scientific interest in the quantification and explanation of tourist trends in absolute terms, that is, of aggregate demand. The main objective of the majority of empirical studies on tourist flows does not focus on their explanation of demand but instead on forecasting. Without reliable forecasts of tourist demand it is difficult, if not impossible, to create developmental plans, or to formulate political solutions in tourism.

Tisdell (2000) summarizes the five reasons why the forecast of tourist demand and the number of tourists is important for mature destination: 1) evaluation of tourism projects; 2) influences on relevant tourism strategies, such as price fixing, the grouping of tourist products or the determination of promotional expense levels; 3) assistance to governments when establishing tax charges in appropriate tourist activities; 4) guideline for governments in the provisions of needed infrastructure and public services to attend to tourists and minimize possible social costs that are generated by tourism; 5) significant variations in tourism demand can have important macroeconomic repercussions on employment and inflation.

Thus, taking into account the undeniable importance of the aggregate forecast of tourist demand, the most referenced typology has been to classify the forecasting methods into three categories: quantitative, qualitative and mixed (see recent developments in tourism demand modelling and forecasting in Song & Li, 2008, and Song et al., 2009). Quantitative techniques are methods that obtain the forecasted values of a studied based on its past evolution or on observed relationships among the forecasted variable and explanatory variables. Thus they are divided into univariate analysis of time series and causal methods. Univariate analysis of time series is based on the identification of historical data patterns using statistical methods and the extrapolation of observed behavior in the past (see Li et al., 2005). All causal factors are considered aggregate, and it is assumed that the net result of these variables is what has caused any tendency, seasonality or cyclical behavior that could exist in the data, and that an extrapolation of the tendency, seasonality or cycle would lead to an appropriate forecast. Among these methods are the naive expectations method, global and local trend adjustment methods, and the ARIMA models (see Box et al., 2008).

Witt & Martin (1987) stated that this type of forecast using extrapolation assumes that the factors that are the principal causes of the observed movement in tourist demand and would continue to be so in the future. Consequently, any change in these relationships would probably result in obtained forecasts that were worse than those produced from other techniques. The second criticism of this type of analysis centers on the lack of incorporation of other variables which the forecasting variable depends on. Nevertheless, this absence could be corrected, at least in part by recurring to transference function models, and also to structured time series models (Harvey, 1989). These models recur to more flexible specifications from the typical components from a time series, as opposed to the traditional deterministic formulation, assuming that each one is stochastic (see tourism demand analysis using structural equation modelling in Turner & Witt, 2001).

Causal methods are quantitative methods that look for explanations for one variable based on other variables that it depends on. Among this type of methods there are econometric models using multivariate regression, based on causal relationships derived from theoretical principles. Nevertheless, specification errors and data measurement can limit their estimating ability, producing comparable results with other models that require lesser effort and are less expensive.

Qualitative methods introduce judgments and expert opinions in tourism and, in particular, of the economic agents that directly intervene in the market —airlines, hotels, tour operators, etc. These techniques are particularly appropriate when past data are insufficient or inappropriate for the study, or when the changes in a previous non-tested stage convert the past data as inappropriate. Among these methods are the Delphi technique and morphological analysis. The Delphi technique consists in reaching a consensus in a group of expert opinions in the subject to be forecasted. The experts are interviewed and later have access to the responses from the other experts, and are given an opportunity to reevaluate their own opinions until the groups reach a consensus for all of the questions. The objective of morphological analysis is to structure the existing information in an ordered form to determine the most probable outcome. In the first stage the most important variables are identified, in addition to the parameters and constraints which affect them. The relationships of these parameters are then determined in order to compare how they perform when combined with the others. The results of these combinations lead to the calculation of demand levels under different assumptions on the variables (see Kaynak et al., 1994). Criticisms of the subjective methods, especially with the Delphi technique, focus on the need to avoid the possible existence of bias on part of the field interviewers, and specifically, in the problem of the appropriate choice of experts and the analysis of the responses, over-pessimism or over-optimism, or the possible inadequacy of the technique to a specific problem.

The third forecasting method category includes mixed methods, which are based on the assumption that neither the purely quantitative point of view nor the exclusively qualitative perspective can properly forecast in any time-space dimension. That is, the short-term forecast is inclined towards the use of time series, while the mid-term and long-term appear to be more appropriate for some of the subjective methods, in spite of their disadvantages.

Some models have developed estimates based on quantitative techniques. Choy (1984), Clewer et al. (1990) and Witt & Witt (1992, 1995) compared the obtained results using quantitative techniques from several different models. From this comparison he came to the following conclusions: 1) It is extremely difficult for any one model to forecast small tourist tendencies. 2) It is not possible to construct one model that is appropriate for all origin-destination pairs, nor one set of explanatory variables. 3) In general, ARIMA models and the assumption that the future does not change with respect to past data —naive expectations— seems to provide forecasts with high levels of precision, while an analysis of the tendency curves reveals that relatively inexact forecasts are given. 4) Exponential smoothing and econometric forecasts are good methods in terms of the change in direction of the tourist demand and of the changes in the trends in the one year time horizon. 5) Structural models from time series have been shown to be just better or even more precise than econometric models, especially if the forecasted time period horizon is not greater than two years. What is clear is that no econometric technique from this group is superior to the rest. Nevertheless, Martin & Witt (1987) and Witt & Witt (1995) indicated that econometric models do have a great advantage over other time series models that are summarized by simply focusing on their definition: the causality that is introduced in the initial term is not considered by the second or following terms.

Witt (1993) pointed out his expectation that other techniques would come along with greater precision that were not only useful to forecast the number of visitors from year to year, but also for a longer horizon. Along this same line of research, Tisdell (2000) states that the emphasis in the short and mid-term could be the result of bias in the research introduced by the market and political systems, and some tourist demand models could benefit from alternative forecasts instead of the traditional ones in Economics, such as the life cycle, the analysis of market segmentation, and the introduction of new variables.

To this context we need to add the limitation of the econometric methods that have been developed at present when trying to determine the internal composition of tourist demand, Internal composition is defined as the proportionality of each individual characteristic, in the form of prior information (nationality, number of nightly stays, expenses, type of lodging, age, sex) about the tourists that visit a destination. This type of disaggregate estimate is essential in mature destinations that have reached the consolidation stage, where the determination of future tourist entrants is not so urgent —it is assumed to be stable—, compared to the knowledge of those individual characteristics of the future tourists that would allow tourist supply to be conveniently adapted and thus avoid important imbalances with the demand which could create a tourist reduction in the destination.

Given the absence of valid tools for the type of required forecast, the implementation of proper genetic algorithms to this context can contribute to cover the present void. In the next section we describe the activation procedure of this method and show its utility as a forecasting tool. The procedure uses an explanatory or implicit argument from traditional economic analysis and can provide a disaggregate vision of demand. Furthermore, it allows individual characteristics of the tourist that has the highest level of satisfaction with his stay to be discovered—something not available in other techniques, that is, a potential repeat visitor and one who encourages other to do the same—, a basic element that the now mature destination needs to continue as an active destination.

4. Computational intelligence and its contribution to economic research

Current developments in information technology have led to a new and dynamic field of research which tackles the understanding and limitations of human behavior. The new area is called Artificial Intelligence, or expert systems, and one of its spinoff branches: Computational Intelligence. Artificial Intelligence is a set of technologies that is able to supply reasoning abilities to a computer that are similar to human intelligence, and importance is given to the use of this technology —what is does. The other branch is called Computational Intelligence and studies the mechanisms of human intelligence that uses any computer science implementation as a simulation tool to validate theories; from this point of view, importance is given to the method — how it is done.

Although there is a clear use of these approaches for a social science such as Economics, significant communication between economists and researchers in Computational Intelligence remains absent. The main reason for this weak interaction lies in the fact that the tools and the objectives of both lines of research are very divergent. Traditional economic forecasting consists in analyzing economic systems with the help of mathematical theory. Economists use a mathematical representation of the model and try to derive analytical results. In order to make these models analytically tractable, the majority of them use behavioral assumptions that are extremely simple. Mathematical analysis then allows ideas and structural explanations of the similarities and differences in the behavior of different formulated models to be given. However, in most cases, they only allow minimal or local results to be obtained. Forecasts using Computational Intelligence offer a very different approach. It tackles the knowledge of the models that can be efficiently implemented in a computer. Usually the mathematical considerations are of minor importance and the algorithms use subjective arguments and similarities with nature. Usually, the analysis of these implementations is performed comparing with a large number from a real problem. The obtained numerical results are used to construct conjectures considering the execution of the implementation in different contexts. In this way, this approximation allows more complex knowledge models to be used although the simulations can only suggest, and not prove, some characteristic of the model.

An artificially intelligent agent —the center of all computational techniques— has greater flexibility than the traditional economic agent. It possesses two obvious advantages over it. In the first place, the artificially intelligent agent is the explicit representation of each individual in the population, which allows that different individuals from a same population have different rules to construct its expectations, and that the researcher can carry out simulations of the evolution of the population under study and observe with detail the behavior of the population faced with new knowledge. The second advantage is that, contrary to the rules found in econometric principles, artificially intelligent agents allow the construction of a basically heterogeneous population of agents that not only differ in their strategies, but also in their behavior when given certain information (Dawid, 1996).

Economic models have frequently represented a population of agents based on a single representative individual. This representative individual carries out his opinions making decisions according to a chosen knowledge rule, thus determining the population state for the next period. Nevertheless, if the expected representative individual is interpreted as the expected average of all the individuals, the best response to this expected average is not, in general, the same as the average of the best responses to the individual expectations. An important effect like this cannot be ignored if representative individuals are only considered instead of heterogeneous populations. In addition, the use of a representative individual only allows the knowledge of the population based on the reaction of the same individual to the observed variables of the system, and prevents a model to be formulated that considers the individual interaction between agents.

Current experimental research on the behavior of economic agents reveals that these deviate substantially and systematically from the ones with premises including formal rationality produce, at least in some areas. Hence, the use of a technique that could establish similarities with the real behavior of the individuals at the moment decisions are made seems to be the most suitable. In this sense, the genetic algorithm is the computational technique that incorporates more evolutionary and adaptive theories in its code.

5. Genetic algorithms and their use to estimate internal composition and tourist demand

Genetic algorithms (Holland, 1975) are considered models of adaptive knowledge and are of particular interest in economics. The interpretation of their different components and parameters from an economic point of view allows theoretical results relative to the behavior of the adaptation process of the agents and additional ideas to be obtained about the relationship between behavior in the model and the characteristics of the knowledge process (Dawid, 1996).

The genetic algorithm is a search algorithm for better solutions —not necessarily optimum ones—, and is especially useful for specific, large scale problems. According to Simon (1982), if this definition is used, the technique found in genetic algorithm is very useful in the economic context since each individual tries to satisfy their needs, and on occasion, can leave feeling satisfied with good actions that are not optimal. If the individual is satisfied he will stop searching for better solutions; otherwise, he will modify some of his actions. Thus, given the adaptive characteristic of the genetic algorithm, the most convenient way to analyze this adaptive behavior of the individual is to formulate a genetic model that allows it to be simulated and analyzed.

Sometimes a solution from a genetic algorithm is optimum and then they are included among optimization methods. Nevertheless, genetic algorithms differ from the traditional optimization procedures in four aspects: a) genetic algorithms work using a codification of the parameters that intervene, not with their own parameters; b) genetic algorithms, starting with a characteristic chain, do not look for only one chain as a solution, but instead a population made up of different chains; c) during their execution genetic algorithms use the information of an associated value for each individual chain; d) genetic algorithms use probabilistic transition rules, not deterministic ones, to guide in the search for solutions.

These four factors contribute to the robustness of the genetic algorithm in specific types of problems and provide an advantage not found in other techniques. Nevertheless, it is also necessary to admit that, in general, the robustness of a genetic algorithm and its efficiency in execution for a particular problem are inversely related, since the more degree of effectiveness of a genetic algorithm in a specific context, the more specialization in this context is necessary. This specialization requires the use of parameters and operators that are especially adapted to the problem at hand, but may not be so appropriate in other contexts (Davis, 1991).

The theoretical foundation of genetic algorithms is based on the genetic processes in training, learning, adaptation and the evolution of biological organisms, especially in the theory of natural selection —or survival of the fittest, according to the expression coined by Charles Darwin (*The Origin of Species*, 1859) —, and in the results of the genetic exchange and the generation of new genetic material by mutation. According to these guidelines, the genetic algorithm is a tool capable of transforming an original population whose artificially intelligent agents are identified by a characteristic vector, to another final population, made up of a specific number of components not necessarily coincidental with the original population, the majority of which have, as expected, similar characteristics to those that, in the original population, were best adapted to the environment and, consequently, most satisfied with it.

Genetic algorithms have been used in economic literature (Arifovic, 1994, 1995; Axelrod, 1984, 1987; Cohen, 1981; Dawid, 1996; Green & Smith, 1987; and Schrodt, 1986, among others); in tourism literature with specific reference to the problem of tourism site location (Hurley et al., 1998); and with forecasting aims (Mahfoud & Mani, 1996). However, the evidence of their application to forecasting aims with real-world data is not as extensive (Hernández-López, 2004, Hernández-López & Cáceres-Hernández, 2007).

Specifically, the genetic algorithm as a method to forecast internal composition of tourist demand is based on the following assumptions: 1) Tourist seeks to maximize his degree of satisfaction obtained from his stay. Such satisfaction is a measure of the correspondence between his expectations before the stay and his final perception after the stay: the higher the level, the greater the degree of satisfaction. The degree of satisfaction is a dependent variable from his personal socio-demographic features such as age, country of origin, length of stay, number of visits, type of accommodation, and services hired. 2) If a tourist is satisfied with his stay —his degree of satisfaction is high— he will probably repeat his stay at the same destination, and he will probably communicate his positive experience. This fact can encourage other tourists with similar features and service needs to visit the same destination. 3) If a tourist is not satisfied with his stay —his degree of satisfaction is low— he probably will not repeat his stay at the same destination, and he will probably communicate his negative experience. This fact can discourage other tourists, whose features and service needs are similar to the first, from visiting the same destination. 4) The genetic algorithm must be redefined if the consumer preferences and the basic components of the tourism supply experience significant changes.

Therefore, the genetic algorithm describes the learning and evolution process which is undergone by the tourism population, where the first-visit of a tourist to a given destination is determined by the information received from a travel agency, publicity, or another tourist, and where the second-visit will be conditioned by the degree of satisfaction from the first-visit (Oppermann, 1998). A genetic algorithm application to an actual tourist population has been performed and has allowed for the forecast the specific features of satisfied tourists who will probably define the medium or long-term definitive tourism pattern of a particular destination.

The underlying idea of the genetic algorithm application is that, on a population of strings or individuals identified by a characteristics vector —initial population— with a certain average degree of adaptation to the environment, it generates another one —final population— with a greater average quality or degree of adaptation. Specifically, genetic algorithms are an effective method to describe as well as to explain the dynamic process that generates changing populations, focused on maximizing the theoretical fitness function. This function involves defining an objective against which each member is tested for suitability for the environment under consideration. In other words, the genetic algorithms fitness function measures the adaptation of any individual. Therefore, the most important problem-dependent aspect in applying genetic algorithms is finding a suitable function in order to determine the fitness of each one of the population members in the genetic population as a function of their characteristics.

Once each member in the initial population has been identified by a characteristic vector and their fitness has been evaluated, the question to answer is how the population can be modified with the objective of increasing its average fitness. Usually, the genetic algorithm modifies the initial population by iterating through the following two phases. In the first phase, the selection procedure chooses individuals from the initial population according to their fitness values, where higher fitness values result in greater probabilities that an individual will be selected. Therefore, this probability determines the expected number of times this individual will be reproduced as a result of the relationship between the size of both the initial population and the final one. The selected individuals define the intermediate population.

However, if the transformation process described by the genetic algorithm adapts the changes occurring in the genetic population to the real ones, then an element of randomness must be introduced in the algorithm, inasmuch as it will permit both the survival of individuals without excessive fitness and the appearance of new individuals. In fact, in the second phase, this element of randomness is introduced by two operators which modify the characteristics of the individuals belonging to the intermediate population. The first one — the crossover operator— involves crossing the two selected individuals at a randomly chosen point. That is, once a point is randomly established in the string using a predetermined probability, the characteristics particular to the right of that point will be exchanged. This technique, the so-called one-point crossover, is the one applied in this research. The second operator —the mutation operator— creates new strings that are similar to current strings. With a predetermined probability, mutation randomly alters some of its characteristics into any of the other values of its rank. It should be noted that the action of the mutation operator could generate a final population with a lower fitness level than the initial one. In order to avoid this undesirable situation, the assumption for mutation probability value has to be sufficiently small.

Most of a genetic algorithms power derives from crossover operators and from simultaneous testing of the strings. The above phases are repeated until the algorithm is halted. The genetic algorithm proceeds for a fixed number of generations or when it satisfies some stopping criterion.

The genetic algorithm code proposed by Hernández-López (2004) is designed according to the simple genetic algorithm of Goldberg (1989) and is specifically adapted to the material in question. Thus, the code developed in this research is a C^{++} version of Goldberg's simple genetic algorithm with several innovations. Firstly, although genetic algorithms are usually applied to a randomly generated population, a suitable and specific heuristic had to be included in order to allow its application to actual data. Secondly, it was necessary to identify the tourists' features in terms of non-binary strings in order to make the code implementation easier, even though the fitness function was estimated using binary strings. In both cases, the strings were based on the explanatory variables. Finally, the use of the fitness function estimation is another innovation since it is unknown beforehand.

Suppose that a tourist population visits a specific destination and that its composition undergoes changes. An increase is expected in the percentage of individuals with similar characteristics to the tourists with highest utility level. The changes are guided by maximization or simply improvement of a hypothetical fitness function. In this case this fitness function could be defined as the tourist's utility level after the stay. Each tourist could be categorized according to a series of characteristics, such as origin country, length of the stay or type of accommodation. So, given a tourist supply, the utility level could be expressed as a function of these characteristics. Once the fitness function is fitted, the genetic algorithm is able to forecast changes in the internal composition of the population in terms of higher or lower presence of individuals with specific characteristics.

The first step in the application of the genetic algorithm consists in formulating a fitness function which provides a value for the utility of the i^{th} tourist, F_i, based on a set of k explanatory variables, $X_i : \{X_{i,1},...,X_{i,k}\}$, which represent specific characteristics of such a tourist. Once the fitness function is obtained, the performance of the genetic algorithm depends on specific operators which specify change patterns in tourism population.

Individuals in the population are identified by structures or bit chains that indicate their characteristics. The algorithm modifies the original population or generation t in two phases. In the first phase, individuals from the original population are chosen using a selection operator and an intermediate population is obtained. The probability that an individual is selected is proportional to the value of the fitness function for such an individual. It is likely that the percentage of individuals with similar characteristics who showed a high utility level will increase in the next time period when compared to the previous time period. The expected number of times that an individual is replicated depends on the relationship between the sizes of the original population and the final one.

In order to obtain an intermediate population of size n the proportional selection operator applies the following procedure. If $\Omega_1 : \{I_{1,1},...,I_{1,r}\}$ denotes the set of individuals in the original population of size r and $W : \{1,...,n\}$ is the set of n positions where the individuals copied from the original population are located, then the intermediate population $\Omega_2 : \{I_{2,1},...,I_{2,n}\}$ is obtained through the selection operator $s(j) = I_{2,j}$, and is defined as $s : W \to \Omega_1$, such that

$$P\left(s(j) = I_{1,i}\right) = P\left(I_{2,j} = I_{1,i}\right) = p_i = \frac{F_i}{\sum_{i=1}^{r} F_i}, \qquad i = 1,...,r, \forall j = 1,...,n \tag{1}$$

where p_i, $i = 1,...,r$, is the probability of copying individual i, that is, the quotient of the fitness of individual i and the sum of fitness of the r individuals in the original population.

The intermediate population is obtained by randomly generating the results of n multinomial tests of size r with probabilities, $p_1,\ldots,p_r$. The copies of the individuals from the original population are completed according to a specified number and a new population is obtained with the desired size. If the selection operator is defined in this way it can be said that it modifies the original population by transforming it into a new population with the hope that this resultant population is characterised by a higher fitness level.

In a second phase, an element of heterogeneity should be incorporated in order to the described transformation process adapts to the observed dynamic adjustment in the population. This element of heterogeneity allows individual whose utility level is not so high to survive in addition to the possibility that new individuals will enter into the population. The crossover and mutation operators (Goldberg, 1989) are normally responsible for the resultant richer population because they allow the characteristics that identify the selected individual in the first phase to be modified. The transformation of the population from these two operators depends on the probabilities that are assigned to them.

However, it should be noted that the transformations that they produce are completely random and not in any way guided by economic statements. In known social settings the automatic application of these operators can lead to the generation of populations whose individuals are defined by incoherent characteristics. In addition, it is possible that qualitative information exists that suggests greater likelihood in certain transformations as opposed to others. It would be interesting to introduce this information when the algorithm is being run. A good strategy may be to maintain the selection operator only to determine the intermediate population. Once the copies have been determined a new strategy should be considered. For example, take the case of a middle-aged English tourist who stays at a 5 star hotel. It is more likely that a middle-aged German tourist who stays at a 5 star hotel will replace him instead of a young French tourist who chooses apartments for his holiday. Qualitative information of this type can be explicitly incorporated into a transition matrix, but it will not be considered if the conventional crossover and mutation operators are used instead. It would be ideal to determine the values of probabilities, p_{ij}, in a hypothetical transition matrix *M* that indicates, for each individual *i* in the intermediate population from the selection, the probability that such an individual is transformed into individual *j* (Hernández-López & Cáceres-Hernández, 2007).

Suppose that *m* individuals exist whose representative strings or structures $E_1,...,E_m$, are different, that is, only m of the n individuals are different in at least one feature. It is assumed that each structure E_i from the original population, or generation *t*, can be transformed into another structure E_j from the final population, or generation *t+1*, with probabilities, $p_{i,j}$, $i,j = 1,...,m$. Of course, $p_{i,j}$ represents the probability that the features of the individual do not change. These probabilities can be placed in a matrix whose *i*th row contain those values $p_{i,j}$ that indicate the probability that the E_i structure is converted into each one of the possible structures, E_j, $j = 1,...,m$. Now let me look at the process of determining the transformation probabilities, p_{ij}. Suppose that the qualitative information about the real population at moment *t* does not result in substantial changes for the next generation at $t+1$. In this case the transition probabilities can be establish by assuming that $p_{i,j}$ is inversely proportional to the number of different characters among E_i and E_j. So, if there is no difference between structures *i* and *j*, $p_{i,j} = \alpha$, $i,j = 1,...,m$, while $p_{i,j} = \beta / \delta_{i,j}$, if the differences between E_i and E_j structures are observed in $\delta_{i,j}$ different features. Obviously, the value of the β parameter depends on the value assigned to α parameter in such a way that $\sum_{j=1}^{m} p_{i,j} = 1$, $\forall i = 1,...,m$.

The transition matrix should, theoretically, be a square and symmetric matrix whose number of rows and columns coincide with the total number of different possible structures that can be observed in the initial population. Nevertheless, bearing in mind the available information on the population, some structures should not be considered in a real specific application of a large dimension. In the same sense, it could be advisable to exclude the presence of a distinct structure in the final population —period $t+1$— which was not observed at moment *t*. According to this hypothesis, the rank of the transition matrix is reduced considerably and the value of β changes for different rows in the matrix because it varies as a function of similarities between each observed E_i structure and the remaining observed structures. A formal definition of the transition matrix is then introduced during the execution of the algorithm as follows.

Let $\Omega_2 : \{I_{2,1},...,I_{2,n}\}$ be a set of *n* individuals from the resultant intermediate population from the copies and let *E* be a set of *m* structures in which each individual in Ω_2 can be transformed. $Q:\{1,...,n\}$ is defined as the set of the *n* positions where individuals from the final population can be placed. This final population $\Omega_3 : \{I_{3,1},...,I_{3,n}\}$ is obtained using the transition matrix operator $tm(q) = I_{3,q}$, defined as $tm(q): Q \to E$, such that:

$$P\left(tm(q) = E_j\right) = P\left(I_{3,q} = E_j\right) = p_{q,j} \quad , q = 1,...,n \quad , j = 1,...,m \tag{2}$$

is the probability that the individual that occupies the q^{th} position in the intermediate population, $I_{2,q}$, is transformed or substituted in the final population by an individual whose structure is determined by E_j. If the individual that occupies the q^{th} position in the intermediate population has structure E_i, then $p_{q,j} = p_{i,j}$, that is, the term in the j^{th} column which corresponds to the row of individual i in the transition matrix. In this way a multinomial test of size *m* with probabilities $p_{i,1},...,p_{i,m}$ can be performed to determine which individual. The probabilities are taken from the i^{th} row in the transition matrix.

The forecasting of the new population from the designed genetic algorithm brings us to the next step. Participation percentages of the future tourist population for each group of identified tourists can be estimated by a given characteristic vector. If the individuals from the population are classified in *m* groups, the forecasting performance of the genetic algorithm can be evaluated with an adjusted goodness-of-fit test in terms of the difference between the observed frequency which corresponds to group *i* in the future population, e_i, and the forecasted frequency for the genetic algorithm that corresponds to the same group, o_i, for each of the *m* groups. In fact, the goodness of fit using transition matrix in genetic algorithm code increases (see Hernández-López & Cáceres-Hernández, 2007).

6. Conclusion

A mature tourist destination can support a regional economy. Thus, it is necessary to care for the tourist product that it offers to potential visitors and allows them to create emotional links with the destination instead of other competing destinations.

Potential tourists to the same destination are neither all alike nor their composition is stable. Thus, it would be more appropriate to consider them as a conglomeration of groups in constant evolution and with a very diverse demand. Then, given the rigidity of the tourist supply to adapt to eventual demands, private and public managers of this important economic activity could reap important benefits from fairly accurate knowledge of not just the number of tourists that are going to visit the destination in the near future, but the characteristics of this population related to different countries of origin, holiday length, type of lodging chosen or expenses during their visit. These characteristics identify the tourist and allow the tourist supply to serve them, in a differentiating way, and the demands from main groups.

In this sense, this chapter has shown that genetic algorithms are able to satisfy this need. Under the basic principle that the composition of a tourist population changes as a function of satisfaction with their stay, that is, higher satisfaction generates more tourists with specific features, the genetic algorithm simulates the evolution in the time that specific components appear or disappear from such a population.

A fitness function is therefore needed and defined which allows the degree of satisfaction of a tourist with its characteristics to be compared. The proposed genetic algorithm forecasts the changes in tourist demand of a destination in terms of the frequency that they are representing individuals with a specific combination of characteristics. In this respect, Hernández-López (2004) offered a design of an adapted version of the well known Goldberg simple genetic algorithm (1989), adapted to the tourism context, which required using a real population of identified individuals by means of non-dichotomy natural attributes such as the initial population.

A genetic algorithm using this implementation contributes clear benefits to the forecast of the internal composition of the tourist demand, but the use of a transition matrix that facilitates the introduction of the economic arguments, such as a guide of the transformations of the chosen individuals in the first stage it has been observed that forecasted results improve. With this objective, Hernández-López & Cáceres-Hernández (2007) implement a genetic algorithm with a transition matrix where traditional cross and mutation genetic operators are substituted by a transition matrix whose elements are the probabilities that any of the structures, or a set of characteristics that define an individual, is transformed into another. In this way, the element of randomness stays in the transformation, however the correspondence can be attained among the expected transformations in a population and the knowledge that it has on it.

In order to conclude, genetic algorithms can be used as a statistic producing tool of a complementary forecast to those obtained with traditional econometric techniques. From a general point of view, the interaction between genetic algorithms and economic analysis presents an advantageous future. The relationship between both of research fields is assured because of the evolutionary theories in economic thought has certainly resurgence in the literature recently. The vision of economic agents that do not pursue optimization in all of its actions, but only in the majority of its cases, that pursue personal characteristics, wishes and objectives only while trying to evolve towards better situations, is something seen in everyday economics and also plays an important role in the basic structure of a genetic algorithm.

The idea developed in this chapter provides opportunities for future research. Firstly, it seems possible to obtain useful information so that the parameters that make up the transition matrix reflect with greater realism the transformation probabilities of some structures in others. This improvement in the transition matrix implies an improvement in the forecasting capacity of the algorithm, and in the measure in which the speed of the implicitly incorporated transformation in these adjusts to the speed of the observed explanatory change in the real population. Note that only the change in the structure of the population of potential tourist service demands have been considered from the tourist service that faces a fixed supply. However, if the supply changes parallel modifications in demand occurs. It is interesting, therefore, to research the formulation of a model that gathers the responses of the demand and the adaptive strategies used in the search for new clients. Along this line, it must be recalled that the change in supply will mean a change in the fitness function, given that the same tourist characteristics will not be associated, in general, to the same level of satisfaction if the environment has changed.

Research in this new area is still in its infancy. Its future could be well linked to the parallel development of statistics and surveys at the local level that propitiate a greater disaggregate understanding of the tourist population expected by tourism suppliers in a destination, without which these types of study cannot contribute meaningful information. More investigations of this type and the use of genetic algorithm in order to know the characteristics of potential tourists in mature destinations are expected in the future.

7. Acknowledgement

The author is grateful to Professor Wanhill, Dr. Alegre-Martín, Dr. Cáceres-Hernández, Dr. López-Martín, Mr Pérez-Pérez, and the anonymous referees for their helpful comments.

8. References

Archer, B.H. & Cooper, Ch. (1998). The positive and negative impacts of tourism, In: *Global Tourism: Second Edition*, W.F. Theobald (Ed.), pp 63-81, Butterworth-Heinemann, ISBN 978-0-750-64022-0, Oxford

Arifovic, J. (1994). Genetic algorithm learning and the cobweb model, *Journal of Economic Dynamics and Control*, Vol.18, pp. 3-28, ISSN 0165-1889

Arifovic, J. (1995). Genetic algorithms and Inflationary Economics, *Journal of Monetary Economics*, Vol.36, pp. 219-243, ISSN 0304-3932

Axelrod, R. (1984). *The evolution of cooperation*, Basic Books, ISBN 0-465-02122-0, New York

Axelrod, R. (1987). The evolution of strategies in the iterated prisioner's dilemma, In: *Genetic Algorithms and Simulated Annealing,* L.D. Davis (Ed.), pp. 32-41, Pitman, ISBN 0-934-61344-3, London

Box, G.E.P.; Jenkins, G.M. & Reinsel, G.C. (2008). *Time Series Analysis: Forecasting and Control* (4th ed.), Hoboken, John Wiley, ISBN: 978-0-470-27284-8

Bull, A. (1992). *The economics of travel and tourism*, Halsted Press, John Wiley and Sons, ISBN 978-0-582-80731-0, New York

Clewer, A.; Pack, A. & Sinclair, M.T. (1990). Forecasting models for tourism demand in city dominated and coastal areas, *Papers of the Regional Science Association*, Vol.69, pp. 31-42, ISSN: 1435-5957

Cohen, M.D. (1981). The power of parallel thinking, *Journal of Economic Behavior and Organization*, Vol.2, pp. 285-306, ISSN 0167-2681

Davis, L. (1991) (Ed.). *Handbook of Genetic Algorithm*, Van Nostrand Reinhold, ISBN 0-442-00173-8, New York

Dawid, H. (1996). *Adaptive Learning by Genetic Algorithms. Analytical Results and Applications to Economic Models*, Lecture Notes in Economics and Mathematical Systems, 441, Springer, ISBN 978-3-540-65607-4, New York

Frechtling, D.C. (1987a). Assessing the Impacts of Travel and Tourism —Measuring Economic Benefits, In: *Travel, Tourism, and Hospitality Research: A Handbook for Managers and Researchers*, J.R.B. Ritchie & C.R. Goeldner (Eds.), pp. 333-351, John Wiley and Sons, ISBN 978-0-471-58248-9, New York

Frechtling, D.C. (1987b). Assessing the Impacts of Travel and Tourism —Measuring Economic Costs, In: *Travel, Tourism, and Hospitality Research: A Handbook for Managers and Researchers*, J.R.B. Ritchie & C.R. Goeldner (Eds.), pp. 353-361, John Wiley and Sons, ISBN 978-0-471-58248-9, New York

Goldberg, D.E. (1989). *Genetic Algorithms in Search Optimization, and machine Learning,* Addison Wesley, ISBN 0-201-15767-5, Reading, Massachusetts

Greene, D.P. & Smith, S.F. (1987). A genetic system for learning models of consumer choice, In: *Genetic Algorithms and their applications: Proceedings of the Second International Conference on Genetic Algorithms*, J.J. Grefenstette (Ed.), pp. 217-223, Lawrence Erlbaum Associates, Inc, Publishers, ISBN 0-8058-0159-6, New Yersey

Harvey, A.C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press, ISBN 978-0-521-40573-7, Cambridge

Hernández-López, M. (2004). Future tourists' characteristics and decisions: The use of genetic algorithms as a forecasting method, *Tourism Economics,* Vol.10, No.3, pp. 245-262, ISSN 1354-8166

Hernández-López, M. & Cáceres-Hernández, J.J. (2007). Forecasting tourists' characteristics by a genetic algorithm with a transition matrix, *Tourism Management*, Vol.28, pp. 290-297, ISSN 0261-5177

Holland, J.H. (1975). *Adaptation in natural and artificial systems.* Ann Arbor. The University of Michigan Press, ISBN 978-0-262-58111-0, Michigan

Hurley, S.; Moutinho, L. & Witt, S.F. (1998). Genetic algorithms for tourism marketing, *Annals of Tourism Research*, Vol.25, No.2, pp. 498-514, ISSN 0160-7383

Kaynak, E.; Bloom, J. & Leibold, M. (1994). Using the Delphi technique to predict future tourism potential, *Marketing Intelligence & Planning*, Vol.12, No.7, pp.18-29, ISSN 0263-4503

Li, G.; Song, H. &Witt, S.F. (2005). Forecasting tourism demand using econometric models, In: *Tourism Management Dynamics: Trends, Management and Tools*, D. Buhalis & C. Costa (Eds.), Butterworth-Heinemann, ISBN 0-7506-6378-2, Oxford

Mahfoud, S. & Mani, G. (1996). Financial forecasting using genetic algorithms, *Applied Artificial Intelligence*, Vol 10, pp. 543-565, ISSN 0883-9514

Martin, C.A. & Witt, S.F. (1987). Tourism Demand Forecasting Models: Choice of appropriate variable to represent tourists' cost of living, *Tourism Management*, Vol.8, No.3, pp. 233-246, ISSN 0261-5177

Oppermann, M. (1998). Destination threshold potential and the law of repeat visitation, *Journal of Travel Research*, Vol.37, No.23, pp. 131-137, ISSN 0047-2875

Schrodt, P.A. (1986). Predicting International Events, *Byte*, Nov., pp. 177-192, ISSN 0360-5280

Simon, H.A. (1982). *Models of Bounded Rationality,* MIT Press, ISBN 978-0-262-19372-6, Cambridge

Song, H. & Li, G (2008). Tourism demand modelling and forecasting – a review of recent research, *Tourism Management*, Vol.29, No.2, pp. 203-220, ISSN 0261-5177

Song, H.; Witt, S.F. & Li, G. (2009). *The advanced econometrics of tourism demand*, Routledge, ISBN13 978-0-203-89146-9, New York

Tisdell, C. (2000). Introduction: Basic economics of tourism: An overview mainly of Volume I, In: *The Economics of Tourism,* C. Tisdell (Ed.), Vol.I, pp: xv-xxxix, The International Library of Critical Writings in Economics 121, Edward Elgar Publishing, ISBN 978-1-858-98403-2, London

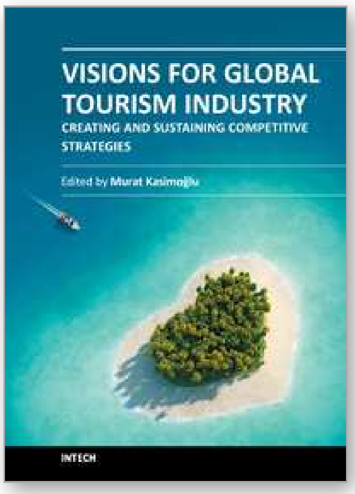
Turner, L.W. & Witt, S.F. (2001) Factors influencing demand for international tourism: tourism demand analysis using structural equation modelling, *Tourism Economics*, Vol.7, No.1, pp. 21-38, ISSN 1354-8166

Witt, S.F. & Martin, C.A. (1987). Econometric models for forecasting international tourism demand, *Journal of Travel Research,* Vol.25, No.3, pp. 23-30, ISSN 0047-2875

Witt, S.F. & Witt, C.A. (1992). *Modelling and Forecasting Demand in Tourism*, Academic Press, ISBN 978-0-127-60740-5, London

Witt, S.F. & Witt, C.A. (1995). Forecasting tourism demand: A review of empirical research, *International Journal of Forecasting*, Vol.11, No.3, pp. 447-475, ISSN 0169-2070

Witt, U. (1993) (ed.). *Evolutionary Economics*, Edward Elgar Publishing, ISBN 978-1-852-78593-2, London



Visions for Global Tourism Industry - Creating and Sustaining Competitive Strategies
Edited by Dr. Murat Kasimoglu

ISBN 978-953-51-0520-6
Hard cover, 478 pages
Publisher InTech
Published online 18, April, 2012
Published in print edition April, 2012

We have been witnessing huge competition among the organisations in the business world. Companies, NGO's and governments are looking for innovative ways to compete in the global tourism market. In the classical literature of business the main purpose is to make a profit. However, if purpose only focus on the profit it will not to be easy for them to achieve. Nowadays, it is more important for organisations to discover how to create a strong strategy in order to be more competitive in the marketplace. Increasingly, organisations have been using innovative approaches to strengthen their position. Innovative working enables organisations to make their position much more competitive and being much more value-orientated in the global tourism industry. In this book, we are pleased to present many papers from all over the world that discuss the impact of tourism business strategies from innovative perspectives. This book also will help practitioners and academician to extend their vision in the light of scientific approaches.