NETWORK ANALYSIS METHODS FOR MODELLING TOURISM INTER-ORGANIZATIONAL SYSTEMS

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ABSTRACT

This paper discusses the emerging network science approach to the study of complex adaptive systems and applies tools derived from statistical physics to the analysis of tourism destinations. The authors provide a brief history of network science and the characteristics of a network as well as different models such as small world and scale free networks, and dynamic properties such as resilience and information diffusion. The Italian resort island of Elba is used as a case study allowing comparison of the communication network of tourist organisations and the virtual network formed by the websites of these organisations. The parameters of these networks are compared to networks from the literature and to randomly created networks. Computer simulation is used to assess the dynamic properties of these networks. The results indicate that the Elba tourism network has a low degree of collaboration between members. These findings provide a quantitative measure of network performance. In general, the application of network science to the study of social systems offers opportunities for better management of tourism destinations and complex social systems.

1. INTRODUCTION

When a researcher chooses a method for studying a phenomenon or a subject, they inevitably make assumptions on the nature of the object of study. These assumptions direct the way the scholar formulates a research question, structures theories and models, carries out their empirical work and interprets empirical evidence. This is also true in the study of tourism. This chapter applies network science as both an innovative approach and a set of methods to analyze tourism destinations. Network science is a well grounded discipline, rooted in the mathematical theory of graphs and statistical physics (Watts, 2004). Network science has been used to uncover the structural and dynamic characteristics of a wide range of systems, from biological organisms through socio-economic groups, to computerized networks (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006). Its application to tourism research however, is relatively new.

The system under investigation is a complex adaptive system (CAS) and includes a large number of elements that relate to one another in a nonlinear fashion. The general characteristics of a CAS emerge from interactions at a microscopic level in a manner not easily predictable by examining the features of the individual elements. Researchers commonly describe a CAS as a network and use graphs to represent the elements of the system and their interactions.

Connections and relationships are among the most important features characterizing the shape and behavior of both the physical and the social world. The majority of the natural and social sciences are, in essence, founded on the study of relationships. As a result, network science is receiving attention from a growing number of scholars interested in researching the structural and dynamic properties of networks. A large part of the systems we examine, including biological cells, organizational communication interactions and linguistic texts can be conceptualized as sets of ‘objects’ connected by ‘links’: in other words, a network.

A review of the network research literature shows that the structure (topology) of a network is a measurable and, at least to some extent, its properties are predictable and affect the overall dynamic behavior of the network. This can be used to explain a wide number of processes including the spread of viruses over a computer network or of diseases in a population; the formation of opinions by members of a social group; the diffusion of information or knowledge; or the robustness of a system to external shocks. These processes all exhibit a strong dependence upon the basic topological features of the network representing the system under study. Network analysis techniques provide diagnostic tools for cataloguing and analyzing the patterns of relationships in networks such as those between groups of people or organizations (Caldarelli, 2007) and may be jointly considered to constitute a new discipline, *network science*. Network science is the study of network representations of physical, biological, and social phenomena with the objective of devising predictive models (Watts, 2004). There are two key research questions in network science: (i) the topological measures used to characterize the properties of a network; and (ii) how these properties affect the behavior or evolution of the systems under study and the processes occurring in them. Answers to these questions, beside their obvious theoretical interest, impact upon our ability to engineer and control a complex system; from improving World Wide Web searches for tourism products to evaluating the risks of ecological damage as a result of human actions through tourism.

The origins of network science are credited to a 250 year old paper by Leonhard Euler (dated 1736) on the Königsberg bridge problem. Surprisingly, these ideas did not find a wider audience until the mid 1990s when the availability and accessibility of data and powerful computation tools allowed scientists to develop effective models, theories and simulations of the static and dynamic properties of networks. Since then, the contribution of scientists from many different disciplines has revealed how behaviors and processes can be described and explained by taking into account a system's general connectivity properties.

Tourism is no exception here, and there is an emergent literature on the importance of the relationships between tourists and service organizations and between tourism companies themselves (Lazzeretti & Petrillo, 2006; Morrison, Lynch & Johns2004; Pavlovich, 2003; Stokowski, 1992; Tinsley & Lynch, 2001). The main focus in these studies is on tourism destinations, thought to be an essential unit of analysis for the understanding of the whole tourism system (Buhalis, 2000; Framke, 2002; Georgulas, 1970; Ritchie & Crouch, 2003; Vanhove, 2005). However, only a few works are available which examine a tourism destination from a network point of view and fewer still use the quantitative methods of network science (Baggio, 2008; Pforr, 2006; Scott, Cooper, & Baggio, 2007; Shih, 2006). When applied to tourism destinations, quantitative network tools can provide a novel view of the destination system and provide managers with the potential to improve functions such as the flow of information or the governance of destinations.

This chapter reviews the application of quantitative methods of analysis to complex networks with an application to the tourism field. The chapter specifically focuses on conceptualizing tourism destinations as networks by enumerating the stakeholders within the destination and the linkages that connect them. The remainder of this chapter is organized as follows. After a brief presentation of the concept of a tourism destination and an historical account of network studies in the wider literature, the chapter provides an outline of the general theoretical framework in which the modern science of networks is embedded. The main models and metrics for a static and a dynamic analysis of a complex network are then discussed along with guidance on interpreting the metrics in the context of a socio-economic system such as tourism. Where possible, examples from the tourism field are given, although examples are also provided from other fields to emphasize the universal applicability of network analysis methods. The methods and results presented here also have the objective of contributing, from an interdisciplinary viewpoint, to the methodological foundation of tourism (Tribe, 1997).

2. TOURISM DESTINATIONS

A tourism destination is “a physical space in which a visitor spends at least one overnight”. A tourism destination includes tourism products such as support services, attractions and tourism resources within one day's return travel time. It has physical and administrative boundaries defining its management, and images and perceptions defining its market competitiveness. Local destinations incorporate various stakeholders often including a host community, and can nest and network to form larger destinations” (UN World Tourism Organization (UNWTO, 2002).

From a more general point of view, this constellation of specialized companies, organizations and communities gathered into a confined geographical location (even if its boundaries are often poorly defined) can be seen as a form of industrial cluster or district. Thus the analysis of a destination’s structure may draw upon the theory of industrial clusters including their mechanisms of formation and their evolution (Hjalager, 1999).

The main models of clusters and networks of companies or organizations have been developed by investigating the manufacturing sector, with limited attention to the service sectors of the economy including tourism. Tourism destinations, however, differ from a ‘traditional’ cluster in a number of respects. For example, they differ in how they are formed,, their focus on the service component, the characteristics of tourism products and their relationships, and the tourism production system itself. Firstly, tourism is essentially a service industry in which the product is not well defined and is composed of many different elements

(Johns, 1999; Sinclair & Stabler, 1997; Wahab & Cooper, 2001). The tourist usually purchases the product in advance and consumes it at the destination. The diversity of elements which form the product requires a range of providers which are an integral component of the same industry (Gollub, Hosier & Woo 2003). Therefore, the traditional models of industrial networks and clusters need modification and adaptation when tourism is the main object of study (Gnoth, 2002, 2006).

Concentration effects in general economic or industrial activities have been studied and measured in detail. Theoretical and empirical research has found that agglomeration effects generally play a crucial role in determining regional income levels (Brenner & Weigelt, 2001; Krugman, 1991), in attracting foreign investment (Barrell & Pain, 1999) and for the competitiveness of the area in which they occur (Norton, 1992). Moreover, economic growth and geographic agglomeration have been found to be self-reinforcing (Martin & Ottaviano, 2001). Concentration of industries increases with economic growth, and in turn by reducing the cost of innovation in the region where the economic activities converge, further enhances growth.

Models of clusters are based on the premise that firms sited in a geographical area share common values, rules and language such that the social environment they form is homogeneous. Social, cultural and operational contiguity favors the spread of tacit information and knowledge among local actors. This constitutes a competitive advantage for the participants in the cluster because this tacit nature of the knowledge makes the information difficult to access by elements outside the community (Morrison, 2004; Norton, 1992). Co-location within a concentrated geographical area is a basis for the development of other characteristics of a cluster. For example, an important factor for a functioning cluster is the formation of close ties or alliances among the different actors and the establishment of co-operation in order to improve the competitiveness of the group beyond the incidental (usually external) effects that promote the gathering (Andersson, Schwaag-Serger, Sörvik, & Hansson, 2004; Mishan, 1971).

At first approximation, a tourism destination is an example of such a collaborative cluster. Mutually dependent attractions, services, transportation and environmental/cultural resources emphasize the need for collaboration, driven mainly by customer demand. As Gunn states (1997: 108): “A traveler is more likely to seek the great diversity and volume of services when they are located together and businesses in such clusters benefit from local as well as travel trade”. Destination clusters generally arise spontaneously and evolve and change over time, driven by both internal and external factors. They are not isolated entities, but open systems with complex linkages to a number of other similar or diverse systems. The development of new products and services is very often done in cooperation with other ensembles, and the interface between different agglomerations allows the creation of new value (Nordin, 2003).

The terms *cluster* and *district* are often used almost interchangeably; however, there are fundamental differences between the two concepts as can be seen in the work of two influential scholars in this field. Industrial *clusters* are “geographic concentrations of interconnected companies and institutions in a particular field” (Porter, 1998: 78). The basic characterizing feature is ‘belonging’ to a specific sector; with the participating firms connected by horizontal or vertical relationships and concentrated within a specific area. Some external entities such as public institutions may complement them, but the focus remains the entrepreneurial and business dimension. On the other hand, the Italian school of research interprets a *district* more widely, as an extension of this specialized spatial concentration. Becattini (1990) adds to the focus on industries, a full recognition of the importance of the social environment of the area in which the district works. He includes regional governments and trade associations and, perhaps more importantly in this age of globalization, the understanding of the role of the linkages with the external world. This broader approach seems to be much closer to the reality of these agglomerations and is much more suitable as a framework for the study of a tourism destination.

However, even taking this broader approach the *district* model needs to be adapted in order to be used as a framework in the tourism field. As discussed above, the tourism product is primarily a service product, with the qualities of intangibility, inseparability, heterogeneity and perishability and therefore different from industrial goods (Vanhove, 2005). In addition, both time and space separate the purchase and the consumption of a tourism product, so that potential visitors are not able to fully assess product attributes prior to consumption (Burns, 1999; Cooper, Fletcher, Gilbert, Fyall & Wanhill 2005; Mill & Morrison, 1992).

A tourism destination, when interpreted as a district, is composed of two main classes of interacting components (Antonioli Corigliano, 1999, 2000; Capone, 2004; Lazzeretti & Petrillo, 2006; Stamboulis & Skayannis, 2003):

1. A large endowment of resources: natural, cultural, artistic, but also artificially built resources such as museums, theme parks or sport complexes; and
2. A network of groups of actors: economic, non-economic and institutional, whose prevalent activity is providing tourism-related services to visitors and travelers.

In a Porterian cluster, the stakeholders of a destination district include only those whose core activity is tourism. However in the tradition of the Becattinian School, the stakeholders would also include the local social system, the various institutional entities (such as local, regional and national government, associations and the community) and other organizations whose activity, although not directly of a touristic nature, is deemed essential for the successful functioning of the system as a tourism destination. In this approach, and in the age of the Internet, the geographical delimitation of the destination can be relaxed somewhat since virtual groupings with entities external to the specific area will be established, thus overcoming the need for a strict physical proximity.

A tourism destination is not a static system but evolves over time passing through different evolutionary phases. The analysis of the development of tourism destinations is an important theme in tourism studies. The literature on this subject is built around the idea of a tourism area life cycle (TALC) originally proposed by Butler (1980). This model is created by applying theories of the evolution of product life cycles to the development cycle of a tourism destination. These theories date from the 1950s and were well established in consumer marketing studies by the time Butler adapted the framework. A new product is launched, achieves acceptance and growth until competitors gain market share (Gardner, 1987); then, innovation or repositioning is necessary to withstand a decline in sales and profits. Butler applies these principles to dynamic, market-driven tourism development and suggests that successful destinations pass through a sequence of growth stages: exploration, involvement, development, consolidation, and then stagnation followed by either a decline or rejuvenation. These stages follow an *s-shaped* logistic curve similar to the one used to describe the general evolution of an industrial district.

The TALC model is effective as a general model of the behavior of tourism districts (Agarwal, 2002; Baum, 1998; Cooper & Jackson, 1989) although it has been subject to a number of criticisms (Butler, 2005a, 2005b). The concept of a tourism destination implies a systematic approach in tourism studies: an approach in which the main focus is on activities and strategies to foster the development of an area as an interconnected system of actors, cooperating in order to supply integrated tourist products to a consumer.

3. NETWORK SCIENCE

The historical development of network science reveals a number of streams of thought (Scott, Baggio, & Cooper, 2008a; Scott, Cooper & Baggio 2007). The first approach is mathematically-based social network analysis, which considers the abstract characteristics and properties of ideal networks as found in the work of Burt (1992; 1997). The second is a qualitative social science-based approach in which a network is viewed as an analogy for the interactions between individuals in a community, such as the policy networks approach of Rhodes (1990; 1997). The third is the physicist's view of complex networks explored in the framework of statistical physics and complexity theory (Albert & Barabási, 2002; Boccaletti et al., 2006). While each of these three streams has advantages for the study of tourism, this chapter focuses on the third stream of thought.

A drawing in which the various elements are shown as dots and the connections among them as lines linking pairs of dots is representative of a network. This drawing, a mathematical abstraction, is called a graph and the branch of mathematics known as graph theory establishes a framework and provides the formal language to describe it and its features. Euler (1736) began this tradition in the 18th century and König (1936) established it more formally at the beginning of 20th century. The tradition provides a broad set of tools for analyzing graphs and the networks represented by them. The application of networks to the social sciences using graphs and related tools (i.e. social network analysis) also developed in the first half of 20th century (Barnes, 1952; Moreno, 1934; Radcliffe-Brown, 1940; Simmel, 1908). The basic idea underpinning social network theory is that the structure of social interactions influences individual decisions, beliefs and behavior (Scott, 2000). Analyses are conducted on patterns of relationships rather than concentrating upon the attributes and behaviors of single individuals or organizations (Wasserman & Galaskiewicz, 1994). By the end of the 1990s, the methods and potential of social network analysis were well established and formalized (Freeman, 2004; Scott, 2000; Wasserman & Faust, 1994; Wellman & Berkowitz, 1988), and network analysis was adopted as a diagnostic tool in applied fields such as management and organization studies (Cross, Borgatti & Parker 2002; Haythornthwaite, 1996; Tichy, Tushman & Fombrun 1979). Social network analysis studies however, while useful, tended to view the social system as static and were often criticized on the basis that they ignored the dynamic nature of organizations and groups.

At the same time, scientists were examining many natural and artificial systems and had documented dynamic behavior that was non-linear and indeed exhibited complex or chaotic patterns over time. This led, in the second half of the 20th century, to detailed study and modeling of such nonlinear complex systems. The consideration of the dynamic properties of networks began in the 1960s with the seminal work of Erdös and Rényi (1959, 1960, 1961) who presented a model of a random network. The authors showed that dynamic growth in the number of connections gives rise to phenomena such as the formation of giant fully connected sub-networks, which seem to arise abruptly when some critical value of link density is attained. This finding attracted the interest of statistical physicists, who were accustomed to the analysis of critical transitions in large systems.

Three provocative papers in the late 1990s placed the analysis of networked systems in the context of statistical physics, providing a strong theoretical basis to these investigations, and justifying the search for universal properties of networked objects (Barabási & Albert, 1999; Faloutsos, Faloutsos & Faloutsos 1999; Watts & Strogatz, 1998). The models proposed in this context have made it possible to describe the static, structural and dynamic characteristics of a wide range of both natural and artificial complex networks. They have also highlighted the linkage between the topological properties and the functioning of a system, almost independent of the nature of the system’s elements (Boccaletti et al., 2006; Caldarelli, 2007; Watts, 2004). There is a growing literature applying these methods to the exploration of social and economic systems, driven by the interest in self-organizing processes and the emergence of ordered arrangements from randomness (Ball, 2003; Castellano, Fortunato & Loreto 2009; Stauffer, 2003).

3.1. Complexity and Network Science: The Theoretical Framework

No formal designation of a complex adaptive system is available despite a growing literature and debate. Instead, many authors characterize a system as complex and adaptive by listing the properties that these systems exhibit (see for example Cilliers, 1998; Levin, 2003; Ottino, 2004). The most common and significant properties are:

- The system is composed of a large number of interacting elements;
- The interactions among the elements are nonlinear;
- Each element is independent of the behavior of the system as a whole, it reacts only to locally available information;
- The system is usually open and in a state far from equilibrium; and
- The history of complex systems is important, their future behavior depends upon this history and is particularly sensitive to it.

Researchers can consider many real world ensembles as complex adaptive systems, and in economics "even the simple models from introductory economics can exhibit dynamic behavior far more complex than anything found in classical physics or biology" (Saari, 1995: 222).

The tourism sector shares many of these characteristics. A tourism destination encompasses many different companies, associations, and organizations and their mutual relationships are typically dynamic and nonlinear (Michael, 2003; Smith, 1988). The response of individual stakeholders to inputs from the external world or from within the destination may be largely unpredictable (Russell & Faulkner, 2004). During the evolution of the destination system it is possible to recognize several reorganization phases in which new structures emerge such as the development of a coordinating regional tourism organization. Besides these particular or unique behaviors however, the system as a whole may follow general laws. Models such as the one by Butler (1980), although discussed, criticized, amended and modified (Butler, 2005a, 2005b), generally provide meaningful descriptions of a tourism destination and, in many cases, prove to be useful tools for managing destination development despite the peculiarities of individual case studies. There are other more detailed studies which assess the 'complex' nature of tourism systems, both in a qualitative and a quantitative way (Baggio, 2008; Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997).

One theoretical framework used to study complex systems comes from the realm of statistical physics and interprets the microscopic behavior of the large numbers of elements which constitute a complex system through macroscopic (statistical) approximations (Amaral & Ottino, 2004). In particular, it provides a theoretical foundation to the study of phase transitions (such as the one that occurs to water when passing from liquid to solid or vapor) and the critical conditions governing them. The statistical physics approach allows for the analysis of data, development and evaluation of models and simulations of complex systems with the help of tools such as nonlinear time series analysis, cellular automata, and agent-based models (see Shalizi, 2006 for an excellent review).

Two important concepts stem from the statistical physics tradition: universality and scaling (Amaral & Ottino, 2004). Universality is the idea that the general properties exhibited by many systems are independent of the specific form of the interactions among their constituents. This suggests that the findings from one type of system may directly translate into the understanding of many others. Scaling laws govern the variation of some distinctive parameters of a system, with respect to its size, and the mathematical expression of these laws applied to complex and chaotic systems involves a power law that researchers now consider to be a characteristic signature of self-similarity.

3.2. Characterization of Complex Networks

Born at the conjunction of disciplines such as physics, mathematics, biology, sociology and economics, network science employs specific terminology and methods. Moreover researchers in this young discipline frequently propose new definitions, algorithms and interpretations, resulting in a lack of consistency and thus creating difficulties in approaching the topic. Boccaletti et al. (2006) and da Fontoura Costa (2007) discuss this situation extensively as do Caldarelli (2007) and Dorogovtsev and Mendes (2003).

Mathematically speaking, a network is represented by a graph G which is an ordered pair $G: = (V,E)$ (Bollobás, 1998). The following conditions apply: V is a set, its elements are called vertices or nodes; E is a set of pairs of distinct nodes, called edges or links. The number of nodes n is called the order of the graph and the number of edges m is called size. The degree of a node is the number of edges connecting it to some other nodes. A node (also called vertex or actor) can represent simple objects (a word in a semantic network) or complex ones (a firm or a biological individual). The latter is used when we want to concentrate on the overall properties of the ensemble rather than on an individual's behavior.

A link (also termed edge or tie) denotes some type of relationship between two nodes. This relationship can include a simple information exchange, a chemical reaction, a force or a road. Links can be symmetric (an information exchange) or directed (a flight from one airport to another) and can be assigned a weight w, that is a measure of strength, importance or value. The characteristics of links are also transferred to the whole graph. We thus speak of undirected (symmetric), directed, weighted graphs or combinations of these (e.g. directed weighted graph). The graph can also be represented by an $n \times n$ matrix A, called an adjacency matrix. If there is an link from some node x to some node y, then the element $a_{x,y}$ has a value different from 0. Its value will be 1 for unweighted graphs, w for weighted graphs. If the graph is undirected, A is a symmetric matrix. There is a full correspondence between a graph, a network and an adjacency matrix; therefore the three terms are used indiscriminately. In particular the identification between a graph and an adjacency matrix brings the powerful methods of linear algebra or use by a network scientist for the investigation of network characteristics. Figure 1 gives an example of different types of networks and their adjacency matrices.

Figure 1 here.

The inter- and multi-disciplinary origin of network science has led, as previously discussed, to a wide variety of quantitative measurements of a network's topological characteristics (see da Fontoura Costa, Oliveira Jr, Travieso, Rodrigues, Villas Boas, Lucas Antiqueira, Viana & Correa da Rocha 2007 for a thorough review). The literature on complex networks commonly uses the following measures to describe a network's structure. In the following formulas: n = number of nodes; m = number of links; k = nodal degree (number of links a single node has); d = distance (length of shortest path connecting any two nodes); the subscript i (or j) refers to a generic node. Based on the adjacency matrix (a_{ij} is an element of the matrix), m and k can be calculated as follows: $m = \sum_i \sum_j a_{ij}$ and $k_i = \sum_i a_{ij}$.

The main network metrics are:

- *density*: the ratio between m and the maximum possible number of links that a graph may have: $\delta = \frac{2m}{n(n-1)}$;

- *path*: a series of consecutive links connecting any two nodes in the network, the *distance* between two vertices is the length of the shortest path connecting is them, the *diameter* of a graph is the longest distance (the maximum shortest path) existing between any two vertices in the graph: $D = \max(d_{ij})$, the *average path length* in the network is the arithmetical mean of all the distances: $l = \frac{1}{n(n-1)} \sum_{i \neq j} d_{ij}$. Numerical methods, such as the well-known Dijkstra's algorithm (Dijkstra, 1959), are used to calculate all the possible paths between any two nodes in a network.
- *clustering coefficient*: represents the degree of concentration of the connections of the node's neighbors in a graph and gives a measure of local inhomogeneity of the link density. It is calculated as the ratio between the actual number t_i of links connecting the neighborhood (the nodes immediately connected to a chosen node) of a node and the maximum possible number of links in that neighborhood: $C_i = \frac{2t_i}{k_i(k_i - 1)}$. For the whole network, the clustering coefficient is the arithmetic mean of the C_i: $C = \frac{1}{n} \sum_i C_i$;

- *proximity ratio*: the ratio between clustering coefficient and average path length normalized to the values that the same network would have in the hypothesis of a fully random distribution of links: $\mu = \frac{C / l}{C_{rand} / l_{rand}}$;

- *efficiency* (at a global E_{glob} or local E_{loc} level): a measure of the capability of the networked system (global) or of a single node (local) to exchange information.

$E_{glob} = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}}$. $E_{loc,i} = \frac{1}{k_i (k_i - 1)} \sum_{l \neq m} \frac{1}{d'_{lm}}$; for the whole network its average (called local efficiency of the network) is: $E_{loc} = \frac{1}{n} \sum_i E_{loc,i}$;

- *assortative mixing coefficient*: gauges the correlation between the degrees of neighboring nodes. If positive, the networks are said to be assortative (otherwise disassortative). In an assortative network, well-connected elements (those with high degrees) tend to be linked to each other. It is calculated as a Pearson correlation coefficient; dg_i is the degree of node i, dn_i the mean degree of its first neighbors: $r = \frac{\sum_i (dg_i - \overline{dg})(dn_i - \overline{dn})}{\sqrt{\sum_i (dg_i - \overline{dg})^2 \sum_i (dn_i - \overline{dn})^2}}$; the standard error can be calculated by using the bootstrap method (Efron & Tibshirani, 1993).

The distribution of the degrees of the nodes of a network is an important parameter of a network topology. This is usually expressed as a statistical probability distribution *P(k)*, that is for each degree present in the network, the fraction of nodes having that degree is calculated. The empirical distribution is then plotted and fit to find a functional (continuous) relationship using a cumulative version of the degree distribution *P(>k)*. This analysis gives the probability (fraction) of nodes having degree greater than a certain value (from the list of the values existing in the network).

A complex network exhibits, in many cases, some form of substructure. Local subgroups can have a 'thickening' of within-group connections while having less dense linkages with nodes outside the group (see Figure 2). The study of this modular structure of *communities* has attracted academic attention, since communities are a common trait of many real networked systems and may be central to the understanding of their organization and evolution. For example, a community's social structure is revealed through the communication patterns within it.

Figure 2 here

Different definitions of modularity exist and researchers in this discipline have proposed several methods to measure it. These methods rely on numerical algorithms that can identify some topological similarity in the local patterns of linking (Arenas, Danon, Díaz-Guilera, Gleiser & Guimera 2004; Danon, Díaz-Guilera, Duch & Arenas 2005). In all of them however, a measure called the *modularity index* is used to gauge the effectiveness of the outcomes (Clauset, Newman & Moore 2004; Girvan & Newman, 2002). It is defined as: $Q = \sum_i (e_{ii} - a_i)^2$, where e_{ii} is the fraction of edges in the network between any two vertices in the subgroup i, and a_i is the total fraction of edges with one vertex in the group. In other words, Q is the fraction of all edges that lie within a community minus the expected value of the same quantity in a graph in which the nodes have the same degrees but edges are placed at random. All of the metrics described in this section can be calculated with the help of standard software packages such as as Pajek (Batagelj & Mrvar, 2007) or Ucinet (Borgatti, Newman & Moore 1992).

3.3. Network Models

After Euler (1736), probably the most important advancement in the study of networks is the work done by Erdös and Rényi. In a series of papers (Erdös & Rényi, 1959, 1960, 1961) they propose a model (ER model) in which a network is composed of a set of nodes and the links are placed randomly between pairs of nodes with probability p. The resulting degree distribution (in the limit of large numbers of nodes and links) follows a Poisson law with a peak ⟨k⟩ (the average degree of the network): $P(k) \approx \frac{\langle k \rangle^k}{k!} e^{-\langle k \rangle}$.

Diameter, clustering coefficient and average path length of an ER network are proportional to the number of nodes and the probability p. The network also shows an interesting behavior when the connection probability increases. Above a certain critical threshold p_c, a giant cluster forms. This giant cluster is a very large group of connected nodes encompassing most if not all of the nodes (depending on the value of $p>p_c$). Below p_c the network is composed of several disconnected subgraphs.

In the late 1990s, three influential papers (Barabási & Albert, 1999; Faloutsos et al., 1999; Watts & Strogatz, 1998) presented empirical evidence of networks exhibiting topological characteristics different from those hypothesized by Erdös and Rényi. Watts and Strogatz (1998) discuss networks in which, contrary to what was expected from an ER model, the clustering coefficient was much higher, and, at the same time, the average path length remained small. Reminding them of the Milgram experiment (Milgram, 1967), they named these networks *small-world* (SW) networks. In a small-world network, as happens in many social networks, any two nodes are likely to be connected through a very short sequence of intermediate neighbors. Many examples of real world networks have this characteristic (da Fontoura Costa et al., 2008).

Figure 3 here.

On the other hand, Faloutsos et al. (1999) and Barabási and Albert (1999) found evidence of networks having a degree distribution quite different from the random Poissonian ER distribution. Their networks exhibit a power-law scaling: $P(k) \sim k^{-\gamma}$ with an exponent $\gamma > 1$. In other words, in their networks, a small fraction of nodes have a large number of immediate neighbors (often called hubs), while a large number of nodes have a low degree (see Figure 3).

These networks are called *scale-free* (SF) because they do not have a distinctive ‘scale’; a typical number of connections per node as is found in a Poissonian ER network in which the average (mean) degree characterizes the distribution. The SF model, first proposed by Barabási and Albert (1999), is a dynamic model. The power-law degree distribution is obtained if we consider a network as formed by adding nodes at successive time intervals, and adding links with a preferential attachment mechanism. A new node will connect with higher probability nodes with high degrees. A large number of real networks demonstrate this kind of rich-get-richer phenomenon although several additions and modifications are required to account for the differences measured between the theoretical model and the real networks.

This basic model is modified in a number of ways: by introducing a fitness parameter which increases the probability that a newly added node will be selected by subsequent nodes; an aging limitation for which a node’s capability to accept connections ends at a certain time interval (age); or an information constraint which puts a limit on the number of nodes a newcomer may connect to. Moreover, even in networks that are not growing by the addition of nodes, links can be added, deleted or moved (rewired) to adapt the network to specific conditions. Thus other mechanisms, besides the preferential attachment family, exist that are able to generate a power-law degree distribution (Albert & Barabási, 2002; Bornholdt & Schuster, 2002; Caldarelli, 2007; Dorogovtsev & Mendes, 2003; Durrett, 2006; Li, Alderson, Tanaka, Doyle & Willinger 2005; Newman, 2003b). Mixed topologies have also been studied, both as abstract models (Mossa, Barthélémy, Stanley & Amara 2002) and empirical observations (Baggio, Scott and Wang 2007; Pennock, Flake, Lawrence, Glover & Giles 2002). The main characteristic of these networks is that they have a degree distribution which follows a power law for the most part, but also has a bending or cut-off point. In statistical physics, power laws are associated with phase transitions (Landau & Lifshitz, 1980; Langton, 1990) or with fractal and self-similarity characteristics (Komulainen, 2004). They also play a significant role in the description of those critical states between a chaotic and a completely ordered state, a condition known as self-organized criticality (Bak, 1996; Bak, Tang & Wiesenfeld 1988). In other words finding a power law is one more confirmation of the complexity of networked systems.

As previously noted, many real networks exhibit scale-free properties. Tourism-related examples include the world-wide airport network (Guimerà & Amaral, 2004); the websites of a tourism destination (Baggio, 2007); the structural properties of inter-organizational networks within destinations (Scott, Baggio & Cooper, 2008b); the paths followed by tourists reaching a destination by car (Shih, 2006); or the world-wide flows of tourist arrivals (Miguéns & Mendes, 2008). Many of these networks also exhibit small-world properties.

This wide variety of network models and empirical cases can be summarized using the classification proposed by Amaral, Scala, Barthélémy & Stanley (2000). These authors use the degree distribution *P(k)* to identify three broad classes of networks:

- *Single-scale*: the degree distribution behaves exponentially (or with Gaussian or Poissonian tails). Members of this class are the random ER graphs and small-world networks. The latter, even if characterized by large clustering coefficients and short average path lengths still exhibit a Poissonian degree distribution;
- *Scale-free*: the dynamic networks unveiled by Barabási with a power-law degree distribution. They are characterized by having few nodes which act as very connected hubs and a large number of low degree nodes. No characteristic mean nodal degree (scale) exists. These networks grow with the addition of new nodes and new links that follow specific mechanisms such as the preferential attachment in which a new node has a higher probability of attaching to an already highly

connected node. This is the case of the tourism web network analyzed by Baggio (2007) and the Australian destinations studied by Scott, Cooper and Baggio (2008b);

- *Broad-scale*: a large class of networks with mixed types of degree distributions. Most of these have a basic power-law shape with a sharp cut-off of the low degree tail (exponential or Gaussian decay). Examples are the airport networks of China (Li & Cai, 2004) and India (Bagler, 2008) or the flow of tourists across countries (Miguéns & Mendes, 2008).

Clearly the literature on complex networks demonstrates the strong relationship between the topological structure and the functioning of the system described. It also provides useful measures of the structural characteristics of the diverse networked systems presented here based on a variety of models.

3.4. Dynamic Processes

A complex system is a dynamic entity: think of economies, companies or tourism destinations as living organisms existing in a state quite far from a static equilibrium. The only time in which they are in a full static equilibrium is when they are dead (Jantsch, 1980; Ulgiati & Bianciardi, 1997; Weekes, 1995). In the literature, the growing interest in development of models for a tourism destination (Butler, 2005a, 2005b), or the numerous methods devised to forecast some characteristic such as tourist demand (Song & Li, 2008; Uysal & Crompton, 1985; Witt & Witt, 1995, 2000) are good testimonials of the dynamic nature of these systems and the appeal of the study of these characteristics.

Analysis of the topological properties of complex networks provides interesting and useful outcomes from a theoretical point of view. It is no surprise to find that this area has received a great deal of attention. The growth processes of all the basic network types discussed in the previous section (the random (ER) graphs and the different types of scale-free networks) have been studied. In this section we describe two dynamic processes which may occur to, and within, a network and which are significant for a tourism destination, our unit of analysis. These are resilience and diffusion of information.

The first characteristic, a system's resilience, is verified in many real-world systems. It is defined as "the capacity of a system to absorb disturbance and reorganize so as to still retain essentially the same function, structure, identity, and feedbacks" (Walker, Holling, Carpenter & Kinzig 2004: 2). In a complex network this can be assessed by looking at how its structural characteristics change when links or nodes are removed from the network. Several numerical simulations have shown that the behavior of a complex network that is under attack is strongly dependent upon its basic topology (Albert, Jeong & Barabási 2000; Boccaletti et al., 2006; Crucitti, Latora, Marchiori & Rapisarda 2004). As an example, the use of the efficiency of a network as a metric to compare different conditions results in a situation similar to Figure 4.

Figure 4 here.

In the case of a purely random removal, the efficiency of a SF network decreases at a much lower rate than an ER network. The scale-free topology adds robustness to the system. When the high degree nodes are targeted, the attack proves to be much more disruptive if the attack is directed toward the hubs of an SF network. Removing just a small fraction of these (less than 15%) can completely destroy connectivity and leave the system as a set of isolated islands. Models based on this type of analysis could explain the resilient behavior of tourism systems after suffering major shocks such as the 9/11 attacks on the USA (see also Baggio, 2008).

A mathematical representation of a system can be used to perform simulations of processes. A simulation can be a powerful tool to create different scenarios and the numerical methods invented have been transformed into computer programs and used in a wide number of disciplines. For systems such as social groups, this technique is, in many cases, the only one available to perform experiments and to study different settings (Axelrod, 2006; Gilbert, 1999; Inbar & Stoll, 1972). Obviously, as the most important literature on the subject reports (e.g. Balci, 2003; Gilbert, 1999; Stauffer, 2003), when a social system is involved some precautions must be taken. In order to ensure the reliability and validity of the results, some conditions must be met: a strong conceptual model is the most important prerequisite, along with the credibility which may derive from the specific techniques used, and the comparison with other analytical results available, or real responses of the system (Adrion, Branstad & Cherniavsky 1982; Balci, 2003). If this happens, numerical simulations of socio-economic systems can provide very effective tools to support management practices. These represent a significant departure in approach from the usual, and open the way for the adaptive approach advocated by those convinced that a tourism destination is a complex, and sometimes even chaotic, system that should be dealt with in a non-deterministic way (Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997; Russell, 2006).

The second characteristic is the diffusion of information through a network. In a tourism destination, the diffusion of information or knowledge is a crucial process for balanced development. Here, the determinants favoring this process are of paramount importance (Argote, Beckman & Epple 1990; Cooper, 2006; Cooper & Scott, 2005). The network effects of this process are well known (Valente, 1995; Wendt & Westarp, 2000), but the possibility of a numerical simulation in the framework of network science can be of great theoretical and practical value.

Figure 5 here.

Consider the diffusion of a message in a network and observe the influence of the network topology. Epidemiological diffusion is a well-known phenomenon for which complete mathematical models have been devised (Hethcote, 2000). It has been known since the work of Kermack and McKendrick (1927) that the process shows a clearly defined threshold condition for the spread of an infection. This threshold depends on the density of the connections between the different elements of the network. However, this condition is valid only if the link distribution is random (as in an ER network). In some of the structured, non-homogeneous networks that make up the majority of real systems such as SF networks, this threshold does not exist (see Figure 5). Once initiated, the diffusion process unfolds over the whole network (Pastor-Satorras & Vespignani, 2003).

4. METHODOLOGICAL ISSUES

Two key issues need consideration in progressing network science and the study of tourism. The first of these is the epistemological legitimacy of applying the laws and methods of physics to a social activity such as tourism. The second relates to the practicalities of collecting data pertaining to a network.

4.1. Epistemology

Applying the laws and methods of physics to a socio-economic system such as a tourism destination may raise an issue of epistemological legitimacy and is an area where there is little relevant prior literature. There is a variety of works dealing with these questions for both natural and social sciences, examining the attitudes and positions of researchers with regard to their approaches and methodologies (Durlauf, 1999; van Gigch, 2002a, 2002b). The specific problem of the applicability of a physical approach to social systems however, is rarely discussed and if so, usually as a secondary topic. Physicists do not seem to feel the need to epistemologically justify their use of the knowledge and tools of physics in investigating other fields. Justifications and discussions are the job of the epistemologist and usually come very late in the development of a field of study. Certainly justifications are not considered necessary when, as in the case of network science, a discipline is still in a very early stage of development.

From a sociologist's perspective however, the application of physical network theory may be rejected as irrelevant because it fails to address the recursive agency in the behavior of groups of people. Recursive agency refers to the ability of individuals to recognize their networked relationships and take proactive steps to change or modify their behavior. Thus, a sociologist may refuse the use of physical laws to model human behavior on the grounds that such laws do not apply.

One of the reasons for this refusal can be that a non-physicist has, sometimes, a mistaken idea of what physics is. Bernstein, Bernstein, Lebow, Stein and Weber (2000), for example, consider that sociologists mistakenly believe that the ideas of physics are mainly those of Newtonian mechanics where single or small sets of particles are studied. Such particles have well defined characteristics (mass, velocity, energy) and their equations of motion can be described and investigated. Consequently, a key objection of sociologists is that a social actor is completely different from these homogeneous particles, and thus the methods of physics are too simplistic a representation to use in social science.

However, the aims of physicists are not about achieving such individual predictive outcomes. In studying a socio-economic system we can focus upon its global behavior and the possibility of making predictions at a system level rather than seeking to predict the conduct of single elements (individual actors). This aim seeks to understand how regularities emerge out of the apparently erratic behavior of single individuals (Majorana, 1942). From this perspective, a comparison of theoretical predictions with empirical data has two key objectives: (i) of verifying whether the trends seen in the data are compatible with a reasonable conceptual modeling of the idealized actors: and (ii) whether there is some level of consistency or if additional factors are required to provide a fuller explanation.

In these circumstances, as Castellano et al. (2009) note, only high level characteristics, such as symmetries, energy balance, or conservation laws are relevant. These, as the findings of statistical physics show, do not depend on the individual details of the system but possess some universal characteristics. Thus, if the aim is to examine such global properties, it is possible to “approach the modelization of social systems, trying to include only the simplest and most important properties of single individuals and looking for qualitative features exhibited by models” (Castellano et al., 2009: 592). These considerations lead us to justify the application of the laws and methods of statistical physics to the study of a socio-economic system such as a tourism destination, with the condition that the quantitative techniques rely on sound and accepted qualitative interpretations of the phenomena as described in this chapter.

The vast theoretical and empirical literature accumulated in recent years has shown network science to be an effective tool for understanding complex systems. The empirical study described in this chapter gives us an example of the application of network analysis methods to a tourism destination.

4.2. Data Collection

Fully enumerating the data relating to the totality of a network (nodes and links) is not possible on many occasions. This failure is especially true for social and economic systems, and is certainly the case for a tourism destination. Using sampling to study complex networks is possible but this requires careful application. Standard statistical considerations apply as long as we are considering a system in which the elements are placed at random, as in the case of an ER network, and where the significance of the sample is assessed with standard methods (Cochran, 1977). We have seen however, in the previous section, that the effects of removing links or nodes from a non-homogeneous system such as an SF network can lead to dissimilar results and is ‘element dependent’. As a result, a sample of a network missing some critical hubs leads to erroneous conclusions about its topology.

The literature on the subject is not extensive. The problem has been highlighted only as a consequence of recent discoveries in the field. It has been found that in the case of a structured network (scale-free, for example) it is not possible to easily determine the significance of a sample collected. Depending on the results of the analysis of the data available, the researcher needs to judge and make an educated guess of the final topology exhibited by the whole population; the whole network. In the cases in which this is possible, then, what can be done is to know how some of the main network metrics vary with the size of the sample and the topology of the network.

For example, according to the literature, in the case of a SF network, degree distribution exponent and average path length decrease when nodes or links are sampled, assortativity coefficient has little or no change and the clustering coefficient decreases when nodes are sampled, but increases when links are sampled (Kossinets, 2006; Lee, Kim & Jeong 2006; Stumpf & Wiuf, 2005).

5. A CASE STUDY: A TOURISM DESTINATION

This section describes a specific case using the network analysis methods described above. The case covers the Italian tourism destination of the island of Elba. Elba’s location is in the centre of the Tyrrhenian Sea and it is a typical sun and sand destination. Elba’s economy depends mainly on the wealth generated by about half a million tourists spending some 3 million nights per year. Elba was selected for study as it is geographically distinct, has accessible records concerning tourism actors and has a scale suitable for detailed examination. The core tourism organizations (such as hotels, travel agencies, associations, public bodies), were identified from the official local tourism board and form the nodes of the network. The connections among them were enumerated by consulting publicly available documents such as membership lists for associations and consortia, commercial publications, ownership and board of directors records. The data obtained and its completeness were validated with a series of structured and unstructured interviews with a selected sample of local 'knowledgeable informants' who included the directors of the local tourism board and of the main industrial associations, or consultants active in the area. These interviews revealed a very limited number of links that were not previously discovered and it seems reasonable to assume that the final network layout has a completeness of about 90%. All the links are considered undirected and of equal weight. The network thus obtained is depicted in Figure 6.

Figure 6 here.

Table 1 summarizes the metrics calculated for this network. As a comparison the second column contains the values calculated for a random (ER) network of the same order and size (the values are averages over 10 realizations). The last column of Table 1 reports typical values for social networks published in the literature (see for example Albert & Barabási, 2002; Boccaletti et al., 2006; Dorogovtsev & Mendes, 2002; Newman, 2003b).

The degree distributions (differential and cumulative) for the network are shown in Figure 7. The shape of the distribution follows a power law $P(k) \sim k^{-\alpha}$. The exponent (and its standard error), calculated following the procedure proposed by Clauset, Shalizi and Newman (2009) is $\alpha = 2.32 \pm 0.27$.

Figure 7 here.

Table 1 here.

The density of links is quite low, considering that the values found in the literature for the social networks studied are typically of the order of $10^{-1} - 10^{-2}$ (Albert & Barabási, 2002; Boccaletti, Latora, Moreno, Chavez & Hwang 2006; Caldarelli, 2007). The percentage of nodes without connections is very high (39%). This results in a sparse network, also confirmed by the small value of the clustering coefficient. The efficiency of the Elban network is consequently quite low, both at a global and a local level. Another value which is different from what would have been expected for a socio-economic network such as Elba, is the assortativity coefficient. This, as seen in section 3, represents the tendency of a node to connect with nodes having similar degrees. The correlation has been found to be positive for many of the social networks examined by the literature (Newman, 2002), and, while debated by some authors (Whitney & Alderson, 2006), this positive correlation is generally considered to be a distinguishing characteristic of social networks with respect to other systems. On the other hand, the calculated values for diameter and average path length seem to be in line with those of other real social systems and sensibly smaller than those exhibited by a random network. This indicates a certain level of compactness of the Elban network, at least for its central connected core. This is also confirmed by the proximity ratio which indicates a good level of 'small-worldness' of the network.

The modularity of the network was calculated by dividing its actors with respect to the type of business (e.g. hospitality, associations, food and beverage services) and geographical location (Elba's municipalities) (Table 2). As a comparison, the modularity was investigated using Clauset et al.'s (2004) algorithm which partitions the network on the basis of its connectivity characteristics, without supposing any division in advance (CNM in Table 2).

Table 2 here.

Table 2 shows the number of clusters identified (groups) and the modularity index. The last row reports the values calculated (CNM) for a network of the same order as the Elban network with a randomized distribution of its links (values are averages over 10 iterations). To better compare the different results, the last column of the table contains the average modularity over the groups (modularity/number of groups). All groups have a very low modularity. In one case (grouping by type), the negative value indicates that the actors tend to have more connections outside the group to which they belong than with businesses within the group. The higher values found by the CNM algorithm confirm that division by geography or by type of business does not imply any strong clustering in these groups. In other words, no well-defined business-type or geographical groupings can be found in the destination. The fact that the randomized network has a lower but similar modularity with respect to that obtained by using the community detection algorithm on the original network is an indication that a distinct modular structure exists even if it is not very well defined or highly significant (Guimera & Amaral 2004). In this socio-economic system, the topology generated by its degree distribution induces a certain level of self-organization which goes beyond pre-set differentiations (by geography or type) of the agents.

5.1. The Topological Analogy: An Example (Real and Virtual)

As a further example of the outcomes of the application of network science to a system such as the Elban tourism network, consider the virtual network among Elban tourism companies. The websites belonging to the tourism stakeholders were identified. Only full websites, with their own address were considered, discarding sets of pages embedded in the portals of other organizations. The web network (WN) was built by listing all the hyperlinks among them. This was accomplished by using a simple crawler and complementing the data obtained with a manual count of the hyperlinks to overcome the limitations of the program used (such as the impossibility of finding hyperlinks embedded in Flash applications or Java applets) (Baggio, 2007). Table 3 shows the topological characteristics of the WN network compared with those of the real network (TN) described in the previous section.

Apart from scale factors, most of the values have differences which are lower than an order of magnitude. Since in a complex network, the distributions of these metrics are not normal, a simple comparison of their averages (arithmetic means) is an insufficient way of establishing similarities or dissimilarities. Here some researchers consider that the Kolmogorov-Smirnov (KS) statistic is able to provide trustworthy results (Clauset et al., 2009; Leskovec & Faloutsos, 2006). The KS D-statistic gives the maximum distance between the cumulative probability distributions of empirical data *F(x)* and *G(x)* over the entire *x* range: $D = \max_x |F(x) - G(x)|$. This statistic is nonparametric and as it is insensitive to scaling issues, it compares only the shapes of the empirical distributions (Siegel & Castellan, 1988).

Table 3 here.

The values for the D-statistics calculated when comparing the distributions of the Web network with those of the real network are the following: degree = 0.119; clustering coefficient = 0.147; local efficiency = 0.125. For comparison, the same values have been calculated for a random sample (RN) of the same size as WN, extracted from the real one. The values (averages over 10 realizations) are: degree = 0.147; clustering coefficient = 0.178; local efficiency = 0.184. The consistently lower values of the D-statistic in the case of the web network (with respect to the random sample) are a good confirmation of the likeness of their structural characteristics.

A strand of literature considers virtual networks as representations of the social relationships among the actors who originating them. In essence: "computer networks are inherently social networks, linking people, organizations, and knowledge" (Wellman, 2001: 2031). Even if some argue that that the links are created in a rather unpredictable way, and it is not possible to find unambiguous meanings (Thelwall, 2006), private or public organizations and companies consider a hyperlink as a strategic resource, and the structure of this network is created by specific aims o communication, rather than by accidental choices (Park & Thelwall, 2003; Vaughan, Gao & Kipp 2006).

Based on these considerations and the network analysis, it is possible to formulate the following conjecture: the network of websites belonging to a cluster of (tourism) companies is a reliable sample of the whole socio-economic network formed by them. The obvious limitation is that the area taken into account must show a significant diffusion of the Internet and the Web. Yet nowadays, for a large part of the World, this is not a severe limitation.

Rather than more or less 'randomly' sampling a socio-economic network with the usual investigation methods (Marsden, 1990), the Web provides us with a relatively fast, easy and objective way of sketching the main characteristics of such networks. The literature has produced much evidence on the issue of network sampling and the effect it might have on the topological characteristics of the whole network (Kossinets, 2006; Lee et al., 2006). This must be taken into account in deriving the insights provided by the methods of network analysis.

5.2. Dynamic Processes

Through their mathematical representation, networked systems are excellent candidates for numerical simulations. Indeed simulation is receiving increased attention as a powerful method to support complex analysis and planning activities for social and economic systems. Information and knowledge flows in a destination are important factors for the general well-being of the system and the manner in which the diffusion unfolds influences the competitive advantage of individual actors and their future planning. Productivity, innovation and economic growth are, in fact, strongly influenced by these processes, and the way in which the spread occurs can determine the speed by which individual actors perform and plan their future actions at the destination. In other words, the structure of the network will be influential in determining the efficiency of the destination's attempts to share knowledge and innovate (Argote & Ingram, 2000).

A computer simulation can help assess the efficiency of information flows across the destination and test the capability of the system to react to changes in its structural parameters. Here, simple epidemiological model can be employed where nodes are either 'susceptible' to receiving information or already 'infected' by it (i.e. they have received it). Despite its simplicity, this model is a reliable approximation and quite suitable to describe a knowledge transfer process (see for example Barthélemy, Barrat, Pastor-Satorras & Vespignani 2005; Xu, Wu and Chen 2007). The simulation was conducted as follows: within a network, one randomly chosen stakeholder starts the spread by infecting a fraction k_i of its immediate neighbors. At each subsequent time step, each infected element does the same until all the network nodes have been infected and the process ends. In this study, the model was run by adopting two different configurations.

In the first case, the capacity of a stakeholder to transfer knowledge (spread infection) is used as a parameter for the model. It is defined as a probability $p(k_i)$ which determines the number of neighbors infected by a single actor. This justifies an important difference between the diffusion of information and knowledge and the spread of viruses. Viruses are indiscriminate, infecting any susceptible individual. Knowledge, on the other hand, is transferred only to a limited set of the individuals with which an actor has interactions (Huberman & Adamic, 2004).

Particular actors then can have different absorptive capacities (Cohen & Levinthal, 1990; Priestley & Samaddar, 2007). Absorptive capacity refers to different capabilities to acquire and retain the knowledge available to an actor due to the associated costs or their internal functioning, and to transfer it to other actors. In tourism, this issue is crucial for the large number of small businesses that typically rely on external contacts for information. In the reasonable assumption that $p(k_i)$ depends on the size of the stakeholder, the network nodes were divided into three classes: large, medium and small (in our case we have the following proportions: large = 8%, medium = 17%, small = 75%). The values for $p(k_i)$ used in the simulations run are (arbitrarily) set as: $p(k_{large}) = 1$, $p(k_{medium}) = 0.8$, and $p(k_{small}) = 0.6$.

The second type of simulation aims at testing the influence of a network's structure, and particularly how the cohesion among stakeholders can affect the knowledge transfer process. In this case the experiment was performed with a modified version of the original network obtained. This was achieved by rewiring the connections while leaving unchanged the original connectivity (i.e. the number of immediate neighbors of each stakeholder and overall density of linkages), in order to obtain a higher clustering coefficient and a higher efficiency. The algorithm used is similar to the one proposed by Maslov and Sneppen (2002). The new network has a clustering coefficient $C = 0.274$ and a mean local efficiency $E_{loc} = 0.334$, as opposed to the original one whose values are $C = 0.084$ and $E_{loc} = 0.104$ (only the fully connected component of the Elban network was used, i.e. all isolated nodes were removed). As a comparison, a random network (same order and density, and random distribution of edges) was used. The time of peak diffusion, which can be used as an indicator of the process efficiency, decreases by 16% when comparing the random network with the Elban network containing different actors' capabilities. This is to be expected, due to the non-homogeneity of the network. When changing to equal capabilities (the original Elban network), a 22% reduction in the time of peak diffusion is found. A further consistent decrease (52%) is found when the local densities (clustering) are increased. Figure 8 shows the cumulative number (as a percentage of total) of stakeholders that are infected as function of time for the different simulations preformed.

Figure 8 here.

Therefore, the interventions made have a significant impact on the information diffusion process. The spread of knowledge is faster if the network's connections are not distributed at random (scale-free in our case), knowledge improves if all the stakeholders have equal absorptive capacities (the maximum) and is even more enhanced when the extent of formation of local groupings (collaborative communities) increases.

5.3. Discussion

The Elban tourism destination network is a complex network whose main traits are common to many other natural and artificial systems. Its scale-freeness has been assessed. Despite this similarity, the structure differs from those exhibited by other complex systems, mainly in its high degree of sparseness and very low degree of local clustering. In tourism terms this means that the local stakeholders exhibit a very low degree of collaboration or cooperation. A quantitative measurement for this feature is naturally derived from the metrics used for the network analysis. In particular, as argued elsewhere (Baggio, 2007), the clustering coefficient (very low in this case) can be used as a measure of the extent of the degree of collaboration, and the assortativity coefficient (very low and negative) can be thought of as representing the tendency to form such collaborative groups. The qualitative knowledge of the destination (Pechlaner, Tallinucci, Abfalter & Rienzner 2003; Tallinucci & Testa, 2006) and the data gathered during the interviews conducted at the destination substantiate the interpretation given. This apparent lack of collaboration among operators belonging to the same type has proved to be detrimental when considering the capacity for innovation which might help the operators face the challenges of the contemporary, highly competitive and globalized market. It has been shown, in fact, that a collaborative approach and intense information exchange, even in seemingly competitive organizations such as the group of Sydney hotels described by Ingram and Roberts (2000), may allow a valuable amalgamation of best practices, with the result of improving the performance and profitability of the whole group and its members. The low level of modularity unveiled further confirms this reading. It is interesting to note that in the results of the analysis, the highest modularity value is obtained with the usage of a generic numeric algorithm (Clauset et al., 2004). This community structure, in the common understanding of the phenomenon (Arenas et al., 2004), can be considered better than those which can be found based on the other criteria used: type of business and geographical location within the destination.

Both the number and the composition of the clusters identified are different (Table 2). The system, in other words, exhibits self-organization properties which lead to the formation, to some extent, of an agglomeration of ties and produces a number of informal communities and an informal community structure. It can be concluded that the information contained in the geographical or business typology data does not fully represent the communality characteristics, and the modularity solutions found in this way are non optimal. Minerba, Chessa, Coppola, Mula and Cappellini (2008) report findings that, for a different social network, support the evidence in the present study.

From a destination management viewpoint, this result is important. The result provides indications on how to optimize performance of aspects of the network, for example, optimal communication pathways or even productivity in collaborations, overcoming rigid traditional subdivisions. The study implies a more practical tool to support the ideas and practices of an adaptive approach to the management of a tourism destination (Farrell & Twining-Ward, 2004).

A word of caution is necessary when considering extending the considerations made on network clustering and modularity to other cases. It has been shown, for example, that significant values for the clustering coefficient can also be accounted for by a simple random graph model (i.e. in which edges are placed at random), under the constraint of a fixed degree distribution $P(k)$. The emergence of this effect is a statistical fluctuation caused by the form of the degree distribution in networks with a finite number of elements (Newman, 2003a; Newman, Strogatz and Watts 2001). A correct interpretation of the result, therefore, can only be achieved by complementing the quantitative assessment with a deep knowledge of the social system under study. Typically this comes from a tradition of qualitative investigation.

Studies of the real and the virtual networks of Elban tourism stakeholders demonstrate the value of the network method for study of a CAS. Even with the limitations discussed previously, it has been possible to formulate a conjecture – the similarity between the topologies of the two networks – which can prove extremely useful in speeding up and easing the process of collecting data to perform network analyses for socio-economic systems such as tourism destinations.

The analysis of this information diffusion process provides us with some more important results. The simulated measurements of the speed of diffusion confirm the improvement in the efficiency of the whole process due to the existence of a structured network instead of a randomly linked system. Two conceptually different situations were simulated. The first considered the stakeholders of the destination as elements with different capabilities to acquire and consequently retransmit information or knowledge. The second assessed the effects of a change in the topology of the network obtained by optimizing it with respect to its efficiency. The results show a clear improvement in diffusion speed when all the actors are considered to have the same capacity to transfer information or knowledge. This is an important finding for destination managers. Putting in place measures and actions aimed at reducing the differences in the absorptive capacities of destination stakeholders can have a highly beneficial impact on the overall system. However, the results indicate that a similar effect, but with an even higher magnitude, can be obtained by optimizing network efficiency. The exchange of information among the nodes is much improved if the connectivity of the network is modified so as to increase the local efficiency, and consequently the clustering coefficient.

An important antecedent for the spread of knowledge in a socio-economic system, such as a tourism destination, is the presence of a structured topology in the network of relations that connect the different stakeholders, and more than that, the existence of a well-identified degree of local cohesion. This conclusion supports the notion that destination stakeholders should form clusters to both compete and cooperate in order to exchange knowledge and hence raise the overall competitiveness of the destination. Quantitative network methods can, therefore, not only assess this effect, but, more importantly, give practical indications on how to improve the process. By performing different simulations with different sets of initial parameters (distribution of absorptive capacities or different levels of clustering), it is possible to obtain different settings and evaluate the effects of the choice of parameters on the final result.

6. CONCLUSION

This paper describes the methods and the techniques that network science provides for the study of complex adaptive systems and as an example of their application, the case of a tourism destination has been discussed along with some of the implications of this approach. Network analysis methods are undoubtedly an intriguing and intellectually stimulating exercise. Physicists know however, that no matter how sophisticated and effective theoretical techniques can be, they have little value when applied to a phenomenon without coupling them with sound physical interpretations. Translating into the language of social science this means that a thorough knowledge of the object of analysis is crucial to obtain meaningful outcomes both from a theoretical and a practical point of view. This knowledge results from applying qualitative methods. As Gummesson (2007: 226) points out, “By abolishing the unfortunate categories of qualitative/quantitative and natural sciences/social sciences that have been set against each other, and letting them join forces for a common goal – to learn about life – people open up for methodological creativity, therefore qualitative and quantitative, natural and social are not in conflict but they should be treated in symbiosis”.

In the 21st Century, the strong focus on issues such as partnership, collaboration, cooperation and the benefits of the tools available for the investigation of the relationships between the elements of a socio-economic system have been discussed in general management studies. The implications go well beyond the simple study of networks. These methods have the strong potential to inform a wide number of concerns such as the use of technology, the study of epidemiological diffusion (from diseases to marketing or policy messages), the formation of consensual opinions and the impacts of these on organizational structure and performance (Parkhe, Wasserman & Ralston 2006).

In this respect, the methods of network science can prove beneficial in deepening the knowledge of the whole system and, coupled with more traditional procedures, can provide powerful tools to enable those adaptive management practices considered by many the only practical way to steer the collective efforts of multiple organizations (Bankes, 1993; Farrell & Twining-Ward, 2004; Holling, 1978; Ritte, Wilkinson & Johnston 2004).

The possibility of using quantitative techniques to analyze the relationships between tourism operators opens new pathways for the researcher interested in the structure, the evolution, outcomes, effectiveness and the governance of the system. This work, therefore, strongly supports the idea that triangulation of research methods can give the clues necessary to improve the analysis of tourism systems and their components (Davies, 2003). Further research in this area will first need to confirm the results obtained so far by increasing the number of examples studied. The methods employed in this chapter clearly require some additional refinement both from a practical and a theoretical point of view. The ever growing number of studies in network science on the dynamic evolution of a complex networked system may suggest new models and new approaches which will need careful consideration before they are applied to the field of tourism. As a final point, it is a firm conviction of the authors that a more rigorous establishment and adoption of methodological tools such as those used in this work can be a powerful way to help tourism research transition towards a less undisciplined array of theories and models (Echtner & Jamal, 1997; Tribe, 1997).

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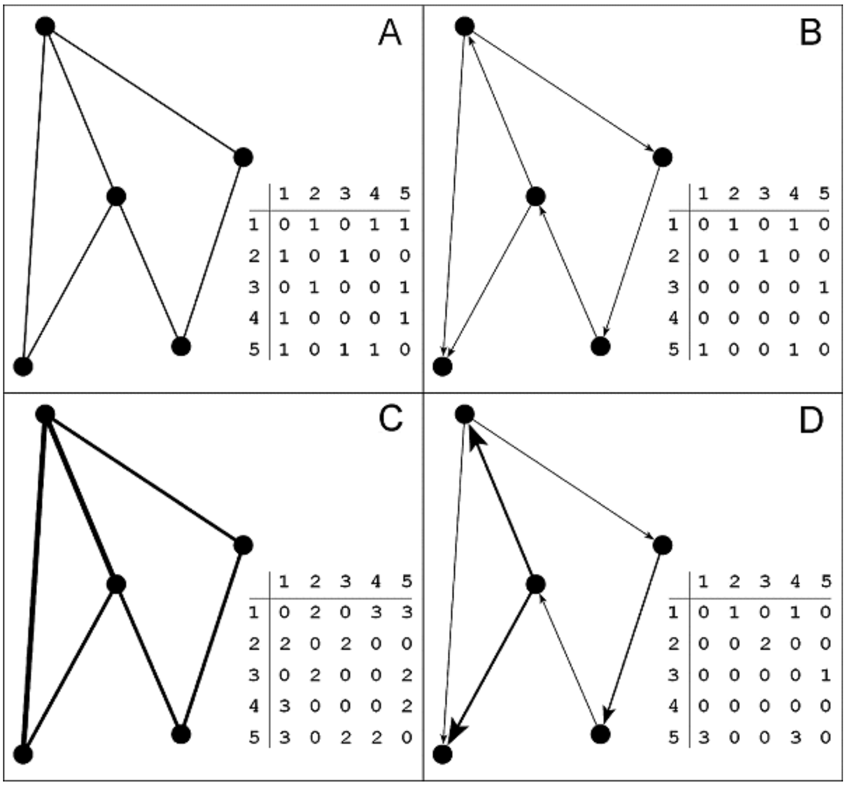

Figure 1 Different graphs: undirected (A), directed (B), weighted undirected (C) and weighted directed (D) with their adjacency matrices

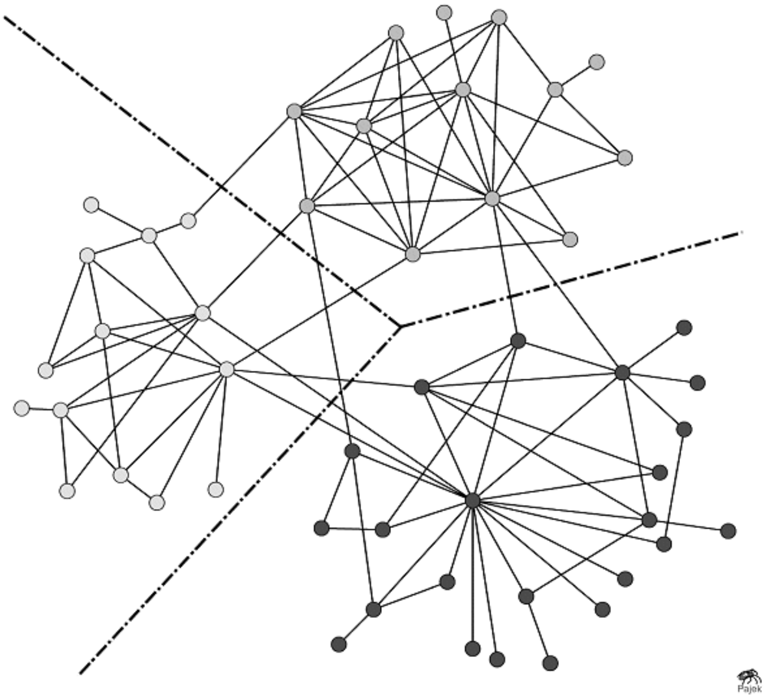

Figure 2 A modular network with a strong modularity (modularity index = 0.57). Dotted lines mark the three communities characterized by having a denser set of links inside them than towards other components of the network

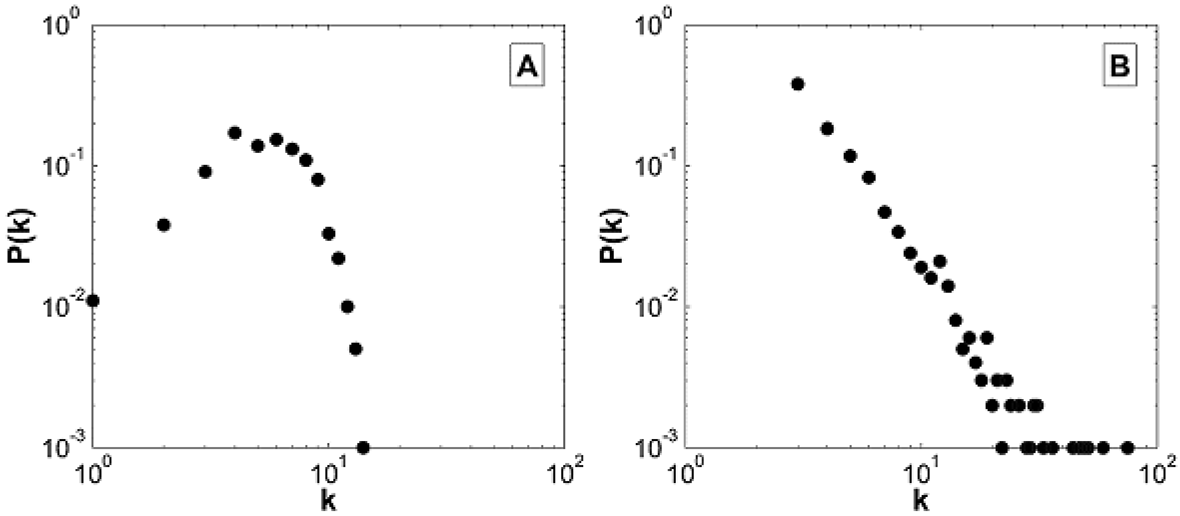

Figure 3 Degree distributions: Poissonian (A) and Power-law (B). The distributions refer to networks of the same order (1000 nodes) and size (3000 links) and are drawn on a chart with logarithmic axes. While the Poisson distribution shows a characteristic curved shape, the power-law distribution is a straight line

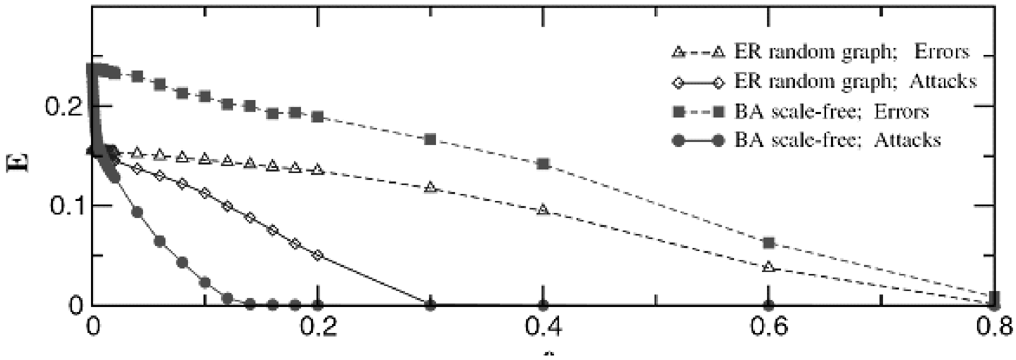

Figure 4 Effects of random (errors) and targeted removals (attacks) for random (ER) and scale-free (BA) networks (f is the fraction removed) on the efficiency (E) of the system (adapted from Boccaletti et al., 2006). The BA network shows a better capacity to absorb random removals than an ER network, but is much more sensitive to targeted attacks to the high degree nodes

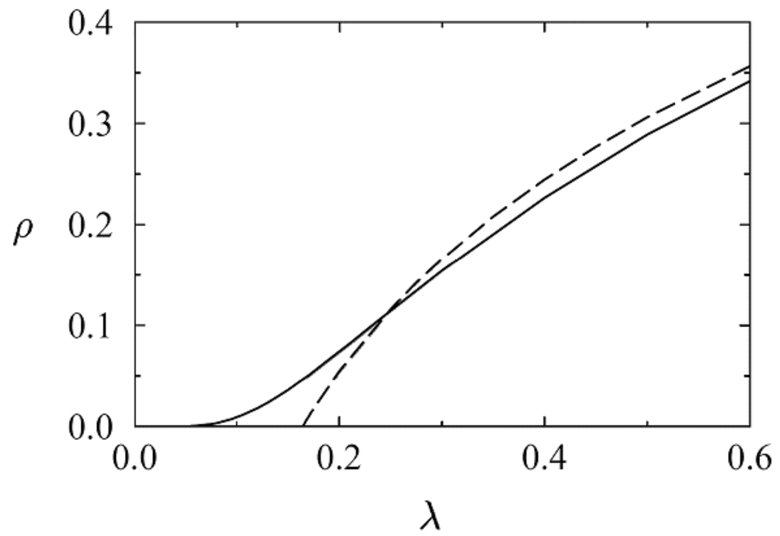

Figure 5 Fraction of infected individuals (ρ) as a function of spreading rate (λ) for a SF network (solid line) compared to an ER network (dotted line) (after Pastor-Satorras & Vespignani, 2003). In an ER network the presence of a threshold for initiating the diffusion is evident while an SF network is lacking a critical onset of the epidemic

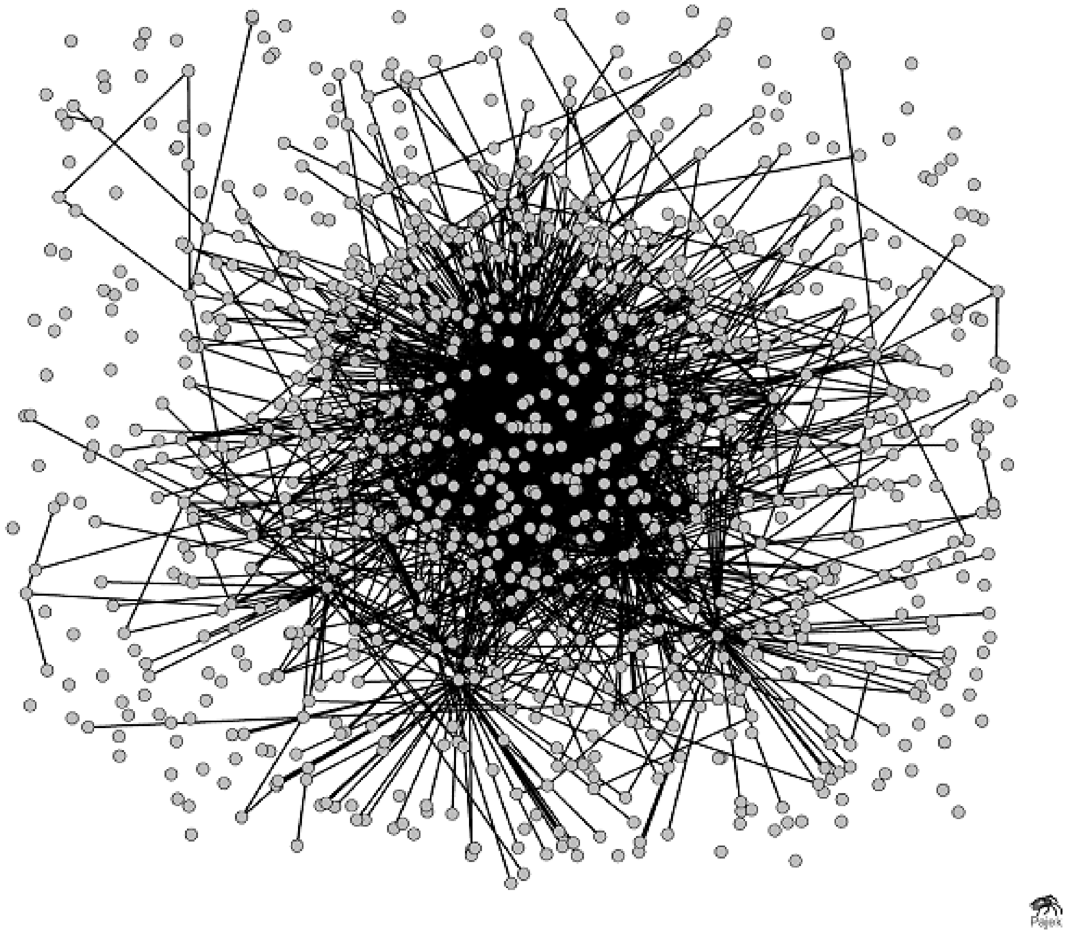

Figure 6 The Elba destination network

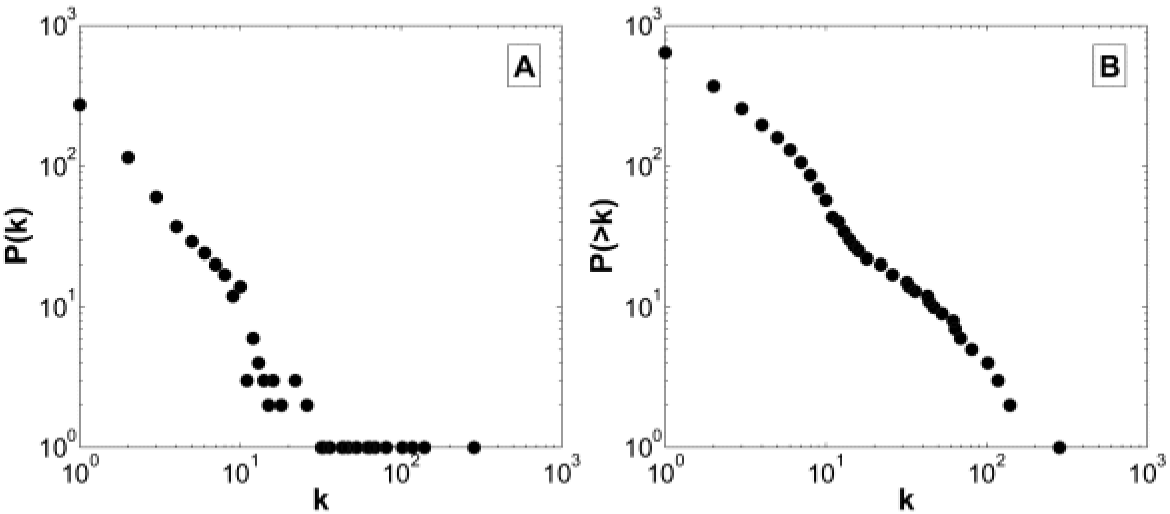

Figure 7 The degree distributions of Elba destination network. P is the frequency of nodes having degree k (A) or greater than k (B, the cumulative distribution)

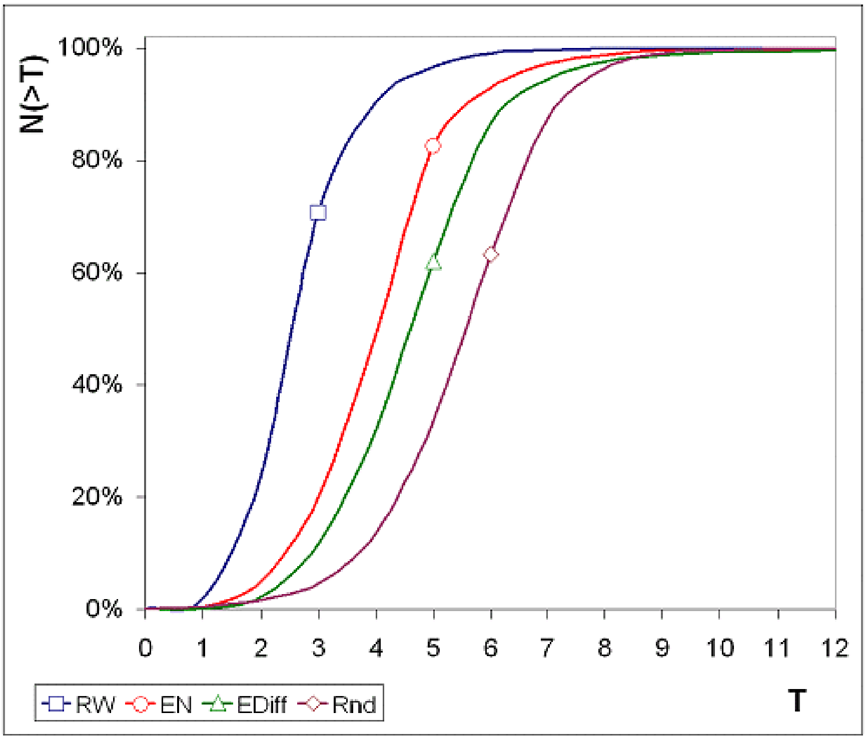

Figure 8 Cumulative percentage of informed stakeholders for the simulations performed: rewired network (RW), Elba network with equal probability of transmission (EN), with probabilities scaled according to stakeholder size (EDiff) and a network of same size with a random distribution of links (Rnd). Curves are averaged over 10 realizations of the simulations.

Table 1

Elba destination network metrics compared with a random network of the same order and size and with typical values for social networks

Metric	Elba network	Random	Social networks
No. of nodes	1028	1028	
No. of links	1642	1642	
Density	0.003	0.003	10^{-1} - 10^{-2}
Disconnected nodes	37%	3%	
Diameter	8	13	10
Average path length	3.16	5.86	10
Clustering coefficient	0.050	0.003	10^{-1}
Proximity ratio	34.09	N/A	10^{2} - 10^{3}
Average degree	3.19	3.25	
Global efficiency	0.131	0.169	10^{-1}
Local efficiency	0.062	0.003	10^{-1}
Assortativity coefficient	-0.164±0.022	0.031±0.033	10^{-1} (>0)

Table 2

Elba network modularity analysis

Grouping	No. of groups	Modularity	Average Modularity
Geography	9	0.047	0.0052
Type	8	-0.255	-0.0319
CNM	11	0.396	0.0360
CNM (random)	12	0.367	0.0306

Table 3

Topological characteristics of the real (TN)

and the virtual (WN) Elban networks

Metric	**TN**	**WN**
Number of nodes	1028	468
Number of edges	1642	495
Density	0.003	0.005
Disconnected nodes	37%	21%
Diameter	8	10
Average path length	3.16	3.70
Clustering coefficient	0.050	0.014
Degree distribution exponent	2.32	2.17
Proximity ratio	34.10	12.21
Average degree	3.19	2.12
Global efficiency	0.131	0.170
Local efficiency	0.062	0.015
Assortativity coefficient	-0.164	-0.167

Table 4 Topological characteristics of the real (TN) and the virtual (WN) Elban networks

Metric	**TN**	**WN**
Number of nodes	1028	468
Number of edges	1642	495
Density	0.003	0.005
Disconnected nodes	37%	21%
Diameter	8	10
Average path length	3.16	3.70
Clustering coefficient	0.050	0.014
Degree distribution exponent	2.32	2.17
Proximity ratio	34.10	12.21
Average degree	3.19	2.12
Global efficiency	0.131	0.170
Local efficiency	0.062	0.015
Assortativity coefficient	-0.164	-0.167