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Knowledge Management and Transfer in Tourism: An Italian Case

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Abstract — Tourism destinations have today a necessity to innovate and remain competitive in an increasingly global competitive environment. A pre-requisite for innovation is the understanding of how destinations source, share and use knowledge. This paper examines the nature of networks and how their analysis can shed light upon how destinations can share and benefit from knowledge as they strive to innovate and be competitive. The paper conceptualizes destinations as networks of connected organizations, both public and private, each of which can be considered as destination stakeholders. In network theory they represent the nodes within the system. The paper shows how epidemic diffusion models can act as an analogy for knowledge communication and transfer within a destination network. These models can be combined with other network analysis approaches to shed light on how destination networks operate, and how they can be optimized with policy intervention to deliver innovative and competitive destinations. The paper closes with a practical tourism example taken from the Italian destination of Elba. Using simulations the case demonstrates how the Elba network can be optimized. Overall this paper demonstrates the considerable utility of network analysis for tourism in delivering destination competitiveness.

Index Terms — Innovation, knowledge transfer, network analysis, tourism destinations.

1 INTRODUCTION

In the twenty first century tourism destinations have an imperative to innovate and remain competitive in an increasingly global competitive environment. A pre-requisite for innovation is the understanding of how destinations source, share and use knowledge. However, the majority of the knowledge management literature and applications are concerned with individual organizations rather than the complex amalgams of organization that characterize destinations. Of course, the focus on the individual organization can be applied to tourism enterprises, destination management organizations and to government ministries and departments. However, if knowledge management is to be an effective tool in tourism innovation, then we also need to consider how it can benefit the destination level of organization. This paper examines the nature of networks and how their analysis can shed light upon how destinations can share and benefit from knowledge as they strive to innovate and be competitive.

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2 KNOWLEDGE AND NETWORKS

There are to date, only a small number of examples and applications of knowledge management across destination networks. However, recognition of the significance of the approach is growing as practitioners recognize the value of knowledge sharing not just within the organization, but also through networks, and in particular the encouragement of partnerships within destinations. It is characterized by the fact that the early phases of knowledge management were characterized by the phrase ‘knowledge is power’. The new thinking argues, ‘Sharing is power’ and creates 'communities of knowledge' at the destination level.

2.1 Destinations as networks of organizations

Tourism more than most economic sectors involves the development of formal and informal collaboration, partnerships and networks. In one Australian study, tourism was found to be the economic sector with the most inter-organizational networks [1]. A significant tourism literature on these topics exists in the discussion of partnerships and collaboration [2], [3], [4], [5] and networking [6], [7], [8], [9]. Indeed one stream of the tourism literature examines tourism [10], destinations [11] and market niches [12] as a system of interrelated components.

The view of destinations as networks is amenable to analysis using techniques such as social network analysis. A social network has been defined as a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the persons involved [13]. Social network analysis delivers a number of useful outcomes. It provides a means of visualizing complex sets of relationships and simplifying them and is therefore useful in promoting effective collaboration within a group, supporting critical junctures in networks that cross functional, hierarchical, or geographic boundaries; and ensuring integration within groups following strategic restructuring initiatives [14].

2.2 Destination stakeholders

A second concept that must be considered in understanding destinations as networks of organizations is that of the stakeholder. The concept is related to changing public sector governance as well as participatory management in the private sector. Stakeholders are the people who matter to a system. A stakeholder is any person, group or institution that has an interest in a development activity, project or program. This definition includes intended beneficiaries and intermediaries, winners and losers, and those involved or excluded from decision-making processes [15].

Stakeholder theory, pioneered by Freeman [16] suggests that an organization is characterized by its relationships with various groups and individuals, including employees, customers, suppliers, governments, and members of the communities. According to Freeman: "[a] stakeholder in an organization is (by definition) any group or individual who can affect or is affected by the achievement of the organization's objectives" (p. 46).

Thus, a group qualifies as a stakeholder if it has a legitimate interest in aspects of the organization's activities and, thus, according to Freeman, has either the power to affect the firm's performance and/or has a stake in the firm's performance. Hence the concept of a stakeholder is related to the concept of participative government and the growth of community activism. Interestingly, identification and consultation with stakeholders originally started as a means of increasing the effectiveness of business but has come to be seen as a matter of business ethics and principles [17].

In the discussion here stakeholders are organizations that have some role in the tourism destination. However all stakeholders are not created equal. Stakeholders may be classified both in terms of their individual characteristics as well as their characteristics in relation to networks. A common approach to classifying stakeholders is to do this in terms of key, primary and secondary stakeholders. Stakeholder analysis is a tool which helps an understanding of how operators affect the creation and dissemination of information in a destination and the resultant policies and activities. It is particularly useful in highlighting the challenges that need to be faced to change knowledge management behavior, develop capabilities and tackle problems.

3 NETWORKS AND KNOWLEDGE TRANSFER

Information and knowledge flows in a destination network are relevant mechanisms for the general behavior of the system. Productivity, innovation and economic growth are 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 [18].

The literature in this field has dealt with two main issues: the mechanisms and the processes of knowledge acquisition within a single stakeholder (e.g. a company, association or group) and the diffusion within the destination network formed by groups of stakeholders, based on their similarity (industrial clusters, for example), or because of their spatial location. The topology of the destination network formed by the different stakeholders and their formal and informal relationships has proved to be an important determinant when explaining the mechanisms by which ideas, information and knowledge 'travel' from one element of the system to another [19], [20], [21], [22].

Social networks are the main channel through which these phenomena unfold. It has been shown in many cases by sociologists and economists that a dense and well formed social network favors a stakeholder's attitude to search for new opportunities and to share experiences, particularly in the presence of dynamic unpredictable environments. This has a beneficial effect on the development of the community in which they are embedded [23], [24], [25]. As an example, Ingram and Roberts [26] describe how the intense web of relationships among managers of Sydney hotels has allowed the amalgamation of many best practices, with the result of improving the performance and the profitability of their hotels. Social network analysis tools have thus been used to study such phenomena and have proved to be effective in explaining the general characteristics of networks [14], [27], [28].

Many theories have been proposed to describe and explain these diffusion processes. The rest of this paper is dedicated to a general overview of them and to the exposition and discussion of a simple simulation model.

4 EPIDEMIC DIFFUSION MODELS

The most commonly used models for the flow of knowledge or information through networks are based on an analogy with the diffusion of a disease [29], [30], [31]. There is clear analogy here between the transmission of disease and the transmission of knowledge through a network. A long tradition of epidemiology studies has dealt with the issue of describing the spread of a disease in a population of living organisms. From Daniel Bernoulli's analysis of smallpox at the end of 18th century [32], mathematical modeling and numerical simulations have helped in the study of the effects of bacterial, parasitic and viral pathogens infections and the possible countermeasures.

The mathematical models used are based on the cycle of infection in an individual. The 'host' is first considered susceptible (S) to the disease. Then, if exposed to the infection it becomes infected (I) and is considered infectious for a certain period of time. Finally, the individual can recover (R) by acquiring some immunity or by being 'removed' from the population. These basic elements (along with some possible variations) are used to characterize the different models which are identified by the initials of the types of infection considered. Therefore, we have SI models, in which hosts can be only susceptible or infected; SIS models in which they go through a complete cycle: susceptible, infected, then susceptible again; and SIR models which consider susceptible individuals that are infected and end their process by being removed (i.e. immunized or eliminated from the initial population). Again the analogy with knowledge flow though a destination network is clear - stakeholders may be susceptible to receiving new knowledge, but until they are 'infected' knowledge transfer does not take place.

The mathematical treatment has much in common with the one used to describe the percolation phenomenon (the diffusion of a fluid through a porous medium). The curves describing the results of the infection are mostly *s*-shaped curves belonging to the family of logistic curves, and are in many cases similar to the ones representing the growth of a population. Traditionally all epidemic models have assumed *perfect mixing*: i.e., all individuals are equally able to infect all others, and have taken into account a random distribution of the contacts between individuals that are responsible for the infection (diseases spread through some kind of contact between the population elements). In some cases the models are refined by making assumptions about the population affected: e.g., the way the hosts react to the infection, recover from the disease or are removed from the population.

Hosts in a population can be represented by the nodes of a network in which the contacts constitute the links. Recent advances in the study of complex networks have allowed a reconsideration of epidemic diffusion models to take into account the effects of non-homogeneous network topologies [33], [34], [35]. These effects are quite important. For example, it has been known for a long time [36] that the SIR model 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 of a random nature, while in some of the structured, non-homogeneous networks that make up the majority of real systems, this threshold does not exist. Once initiated, the diffusion process unfolds over the whole network [34].

The formulation of an epidemiological model leads to the layout of a system of differential equations which can be, at times, uneasy to deal with. In the last few years however, the availability of computational tools (both hardware and software) has fostered the development and the usage of numeric simulation models. In what follows we shall use this approach to analyze a tourism case taken from Italy.

5 NETWORK MODELS

A long tradition, prompted by the 1736 paper by Leonhard Euler on the Königsberg bridges, has provided a widespread set of mathematical tools for analyzing networks and the graphs they represent. During the 20th century, the ideas and techniques developed for the study of these abstract objects have been applied to several fields. In particular, realizing that a group of individuals can be represented by enumerating the stakeholders of the group and their mutual relationships, sociologists have used some of the methods belonging to graph theory to study their patterns of social relations [37], [38]. Furthermore, in the last decade, the community of physicists and mathematicians have exploited the vast amount of data available through the Internet to develop a whole new set of models. With these it has been possible to describe the static, structural and dynamic characteristics of a wide range of both natural and artificial complex networks [39], [40].

Today's network science toolbox comprises a rich set of metrics [41], originating from the combination of those coming from the tradition of social network analysis with the outcomes of the recent work. Some of the following measurements are, reputedly, important to fully characterize topology and behaviors of a complex network and can be applied to destinations:

- *degree distribution P(k):* the statistical distribution of the number (and sometimes the type) of the linkages among the network elements;
- *average path length L:* the mean distance between any two nodes and diameter D: the maximal shortest path connecting any two nodes. Small values for D and L indicate good compactness of a network; at least, of its main connected component;
- *clustering coefficient C:* representing the concentration of the connection of the node's neighbors in a graph and giving a measure of the heterogeneity of local density of links;
- *efficiency* (at a local E_{loc} or global E_{glob} level): which can be interpreted as a measure of the capability of the system to exchange information over the network; and
- *assortativity*: which gauges the correlation between the degrees of neighbor nodes. If positive, the network is said to be assortative. In such a network, well-connected elements tend to be linked to each other. This quantity, connected to the clustering coefficient, has been recently shown to directly influence the formation of strongly connected sub-networks or communities and to give an indication of their strength [42].

The mathematical expressions for these quantities can be found in one of the recently published reviews of the research in this area [39], [43].

5.1 Computer simulations

In addition to describing and explaining phenomena, numerical simulations allow experiments to be performed in fields where these would not otherwise be feasible for both theoretical for practical reasons. A network is a system which may comprise a very large number of elements and its topological characteristics have a direct relationship with many dynamic processes. It would be therefore be interesting to experiment with different configurations to measure these effects in order to better understand how these differing configurations influence the behavior of the whole destination system.

Social scientists have long used simulation techniques [44]. The wide availability of computing power and of efficient programming languages, coupled with a much simpler access to data has, in recent decades, greatly enlarged the amount of attention given to these methods and their practical uses [45], [46], [47]. A widely used environment to perform simulations is the series of toolkits developed to implement agent-based models (ABM). The idea of such simulations is that a system is composed of a number of entities (agents) which behave according to some simple rule [48, 49]. The interactions of the agents can generate some global system property which can then be studied. Variations in the basic rules or in the typology of the agents produce different final configurations for the system. The reliability and credibility of these techniques is generally considered good, provided some basic requirements are met: as recognized in the literature, the most important being the usage of a solid conceptual model and the connection with the particular circumstances for which the simulations are run. In other words: no absolute value can be given to such processes, as their value will be dependent on the specific situation or the specific purpose [50], [51], [52]. With these caveats, these models have proved to be quite effective and efficient in reproducing different types of social and natural systems and may be considered a valuable aid in decision making [53], [54]. A number of dedicated programs have been developed to help with ABM simulations, and specialized software packages provide libraries with functionalities at different levels of complexity.

6 THE DESTINATION NETWORK OF ELBA, ITALY

Based on the above discussion, we can consider the diffusion of knowledge in a tourism destination as an ‘infection’ process in which knowledgeable individuals (in our case the destination stakeholders) transfer their knowledge to the other members of the social group with which they have contact. Configuration of the network and the nature of the stakeholders would be expected to influence the efficiency of this process and thus, ultimately, the destination’s ability to innovate and be competitive.

The island of Elba, Italy, is part of the Tuscany Archipelago National Park and the third Italian island. It is an important environmental resource owing to its geographic position, temperate climate and the variety and beauty of its landscapes, coast and sea. It is a sea, sport and culture destination, with almost 500,000 arrivals, 3 million overnights per year and several hundred accommodation establishments. Elba is considered a ‘mature’ tourism destination [55], [56] with a long history and which has gone through a number of different expansion and reorganization cycles. The great majority of the stakeholders are small and medium sized companies (SMEs), mostly family-run. Several associations and consortia operate on the island in an attempt to overcome the excessive ‘independence’ of companies by suggesting and developing different kinds of collaboration programs.

The network considered here is the one formed by the websites belonging to Elba’s tourism operators. In taking this network as a basis, we make the assumption that the connections among the websites (hyperlinks) may be regarded not only as a ‘simple’ technological manifestation but also as a reflection of social processes. The structure of hyperlinks form patterns based on the designs and aspirations of the individuals or organisations who own websites. A growing literature suggests that these networks reflect offline connections among stakeholders and support specific social or communicative functions [57], [58], [59].

Even considering the warnings, and the limitations on the validity of this type of interpretation as discussed by Thelwall [60], it is reasonable to assume that in the case of the websites of commercial companies (especially for the importance given to the practice of hyperlinking [61]) the layout of the network can represent the structural characteristics of the social system from which it originates. This relationship between cyberspace and the physical world is bidirectional: on the one hand, the online linkages represent and complement social relations in the offline world; whilst on the other hand, offline interactions can influence the way in which online relationships are established and developed [62], [63].

The analysis of the main characteristics of the Elba network can be summarized as follows [64], [65]:

- the network shows a scale-free topology (power-law behavior of the degree distribution) which is consistent with that generally ascribed to many artificial and natural complex networks;
- the general connectivity is very low (link density) with a very large proportion of disconnected elements;
- clustering is quite limited, as is the efficiency, both at a local and global level.

These results provide quantitative evidence in favor of recognizing that the ‘community’ of Elban tourism operators is fragmented in nature. There appears little incentive to group or cluster in a cooperative or collaborative manner as evidenced by considering the clustering and assortativity characteristics. These conditions are also problematic for an efficient flow of information and knowledge through the social system, and this may affect its capabilities to innovate and future competitiveness. These considerations are in general agreement with previous studies performed by using more traditional qualitative techniques [55].

6.1 Simulating knowledge flow in the Elba network

The Elba network can be used to perform a simulation of the transfer of information and knowledge across the network. Our objective is to assess the present situation and to test the capability of the destination network in absorbing the knowledge transferred when changing some of its structural parameters.

In our simulation a simple SI epidemiological model is used. Despite its simplicity, this class of model has shown to be quite effective and to be a good approximation of more refined and complex models [66], [67]. In addition, it is suitable for describing the knowledge transfer process. In fact, we may well reasonably assume that once knowledge has been transferred to a new host, it will retain the knowledge received, therefore it will remain infected. This is an essential pre-requisite to innovation as unless the knowledge is transferred and used by enterprises at the destination, innovation will not occur.

The algorithm used for the simulation is the following:

1) the network is loaded;
2) one randomly chosen stakeholder starts the spread by *infecting* a proportion k_i of its immediate neighbors. In tourism, this stakeholder is often a government-funded tourist board or economic development agency;
3) at each time step the infected elements transfer the knowledge to a proportion k_i of their immediate neighbors; and
4) the process ends when all the network nodes have been infected.

As a parameter for the model, the capacity of the solitary stakeholders to transfer knowledge is used. It can be expressed as a probability k_i, whose value controls the number of neighbors which are informed by a single stakeholder. This accounts for an important difference between information and knowledge flows and the spread of viruses. While viruses tend to be indiscriminate, infecting any susceptible individual, knowledge is selective and is passed by its host only to a limited set of the individuals with which it has relations [68]. Moreover, particular actors can have difficulties in acquiring and retaining all the knowledge available to them (a feature usually called absorptive capacity, see for example [69], [70]) due to their internal functioning or because of the associated costs. In tourism, this issue of absorptive capacity is critical, particularly given the dominance of SMEs in the sector.

We can assume that the capacity of transferring knowledge is different for the different 'sizes' of companies involved. Therefore, the network nodes have been divided into three categories: large, medium and small. In our case we have the following proportions: large = 8%, medium = 17%, small = 75%. The values for the proportion of neighbors informed used in the simulations run are (arbitrarily) set as: $k_{large} = 1$, $k_{medium} = 0.8$, and $k_{small} = 0.6$. Since the structural characteristics of the network, and particularly the cohesion among stakeholders, can be a factor influencing the knowledge transfer process, the experiment has also been performed with a modified version of the original network [24, 71]. This has been obtained by rewiring the connections while leaving unchanged the original connectivity (i.e. the number of immediate neighbours of each stakeholder and overall density of linkages), in order to obtain a higher clustering coefficient. The algorithm used is similar to the one proposed by Maslov [72]. The new network has a clustering coefficient = 0.08, as opposed to the original one whose value is 0.02. It should be noticed that both values are still very low compared to the ones reported by the literature for social networks [40], [73].

A synthetic network of the same size (with respect to the number of nodes and link density) but with a random distribution of links is used as a comparison in this case. The model has been implemented with Netlogo [74] and is a derivation of some of the distribution library models (Rumor Mill as modified by F. Stonedahl http://www.cs.northwestern.edu/~fjs750/netlogo/).

6.2 Results and discussion

The first series of simulations considered the stakeholders' capacity to transfer information and knowledge. The results are shown in Fig. 1 and Fig. 2. Fig. 1 depicts the cumulative number (as a percentage of total) of stakeholders that are 'infected' as function of time. Fig. 2 is the differential version, i.e. the number of informed actors at each time interval.

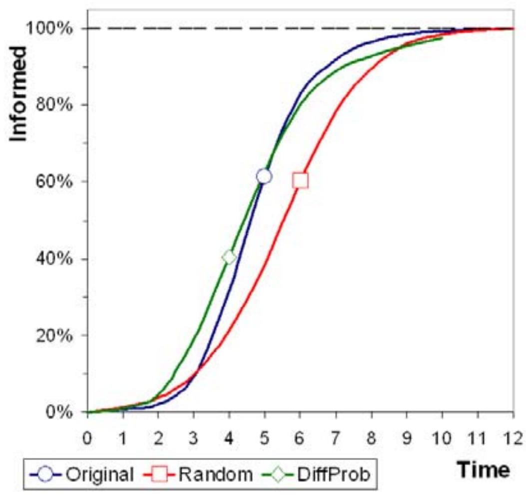

Fig. 1 Cumulative percentage of informed stakeholders with equal probability of transmission (Original), with probabilities scaled according to stakeholder size (DiffProb) and a network of same size with a random distribution of links (Random). Curves are averaged over 10 realizations of the simulation.

As can be seen, there is only a limited difference between the two situations. It looks as if the varying capability of tourism stakeholders to transfer knowledge to other members of the community does not affect, in a sensitive way, the whole diffusion process. This can be partly due to the distribution of stakeholders' size. In fact the great majority (75%) are small companies, and these mainly govern the diffusion mechanism. The comparison with a 'random' network reinforces the idea that the structure of the social network has a noticeable impact on the phenomenon studied.

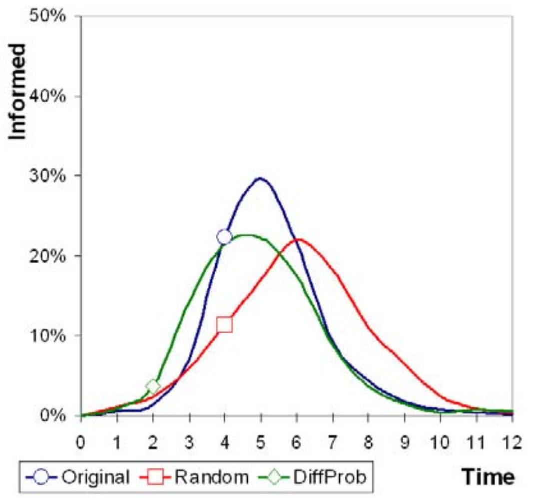

Fig. 2 Differential curve of knowledge spreading for stakeholders with equal probability of transmission (Original), with probabilities scaled according to stakeholder size (DiffProb)) and a network of same size with a random distribution of links (Random). Curves are averaged over 10 realizations of the simulation.

The 'topology' effect described above is much more evident in the second series of simulations whose results are depicted in Fig. 3 and Fig. 4. In this case the model has been used by changing the structure of the actual network. The first run is based on the original network, the second on a rewired version having a much greater clustering coefficient, i.e. a much greater degree of local cohesion among the tourism stakeholders. An unstructured homogenous random network has been employed as a comparison. The difference is clearly identifiable. The knowledge diffusion process is much faster in the case of a structured network (e.g. the power-law distributed Elba network) than in the random one, and almost the same improvement in speed can be observed when considering the increase in clustering.

We must therefore conclude that a very important determinant 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 supports the notion that destination stakeholders should be encouraged to form clusters and to both compete and cooperate to raise the overall competitiveness of the destination. Often the public sector intervenes to initiate such cooperative processes, given the combative nature of SMEs. However, public sector support can facilitate a network and provide ongoing support, but it is the destination stakeholders who must operate the network.

These results are not completely new. The effect is the one identified by [75], [76] as the *strength of weak ties* and reconfirmed by the more recent works on the so-called *small world networks* [77], [78], [79]. Moreover, several authors have empirically found this behavior [71], [80]. Here, for the first time, a tourism destination is used as test case.

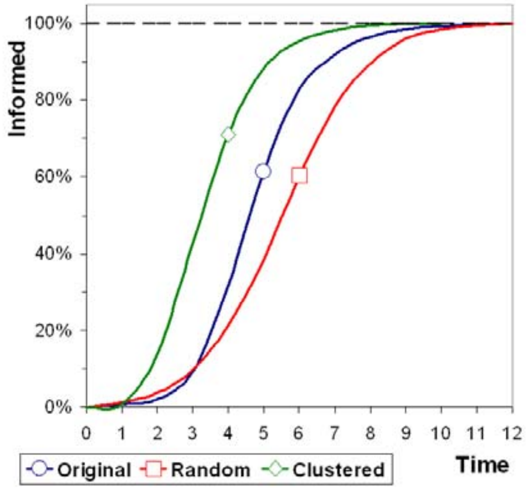

Fig. 3 Cumulative percentage of informed stakeholders for the Elba network (Original), the network rewired with higher clustering coefficient (Clustered) and a network of same size with a random distribution of links (Random). Curves are averaged over 10 realizations of the simulation.

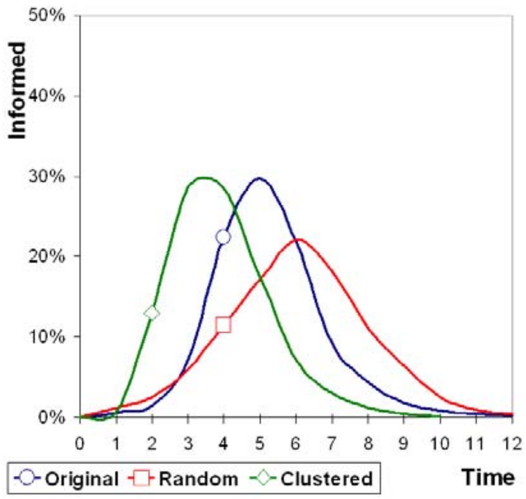

Fig. 4 Differential version of the knowledge spreading curves for the Original, Clustered and Random networks. Curves are averaged over 10 realisations of the simulation.

By coupling these theoretical and analytical approaches with a thorough understanding of the destination and its stakeholders, we can diagnose the efficiency of the destination's network structure and its implications for competitiveness. We can also begin to utilize policy instruments to intervene and to make the network more efficient. In other words, in a case such as Elba, the simulations can be used to create development scenarios in which the efforts to move towards strong forms of collaboration are increased, even if at a very 'local' level, it can be highly beneficial not only for the stakeholders involved, but for the whole destination.

7 CONCLUDING REMARKS

This paper has outlined the benefits of importing analytical and theoretical techniques of network analysis to tourism destinations. The benefits are clear. In a knowledge economy, destinations have to innovate to remain competitive. Knowledge management is the engine of innovation and an understanding of how knowledge can be managed across complex network organizations is fundamental to this process. For tourism, as has been seen, a particular concerns is the fact that most destinations are comprised of SMEs, organizations which tend to be knowledge averse and therefore public sector intervention is needed to establish cooperative frameworks at the destination level. In other words, the theoretical interest in understanding the processes of knowledge transfer in a complex system such as a tourism destination is undoubtedly of interest from the point of view of practitioners.

The methods and the techniques used in this paper have shown that, once accepted, important 'network' framework results can be derived by studying a specific system. The basic analytical tools allow an assessment of the peculiar characteristics of the structure and functioning of a destination. Computerized numerical simulation models based on the theories of a network can deliver differing development scenarios and show how the system would evolve. It should be observed, however, that the quantitative tools and methods used here are not fully sufficient to provide a full range of results. Knowledge of the specific destination under study combined with qualitative assessments of the sector and local policy can greatly add to the toolbox available to tourism scholars and practitioners, and in turn, better equip them in their effort to understand the complex systems that are tourism destinations.

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