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Modeling commuting systems through a complex network analysis

A study of the Italian islands of Sardinia and Sicily

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Abstract: This study analyzes the inter-municipal commuting systems of the Italian islands of Sardinia and Sicily, employing weighted network analysis technique. Based on the results obtained for the Sardinian commuting network, the network analysis is used to identify similarities and dissimilarities between the two systems.

Keywords: Complex networks; Commuter dynamics; Weighted networks

1 Introduction

Commuting—the habitual act of leaving one's home and traveling to work—has been the focus of a variety of multidisciplinary research studies (Horner 2004). In recent decades, transportation systems have improved to the point that many more citizens are now able to live far from their work place and to have access to a number of attendant benefits, such as reduced levels of congestion and pollution (Limtanakool *et al.* 2006; Nielsen and Hovgesen 2008; Sandow 2008; Xu 2001). Mobility patterns, and in particular commuters' behavior, are determined by—and affect—land use policy and physical planning. This was confirmed by Sohn (2005), who observed that spatial patterns of residential and employment locations can be verified by a systematic study of commuting. As many studies have pointed out (see Grazi and van den Bergh 2008), spatial organization mechanisms together with policy and planning instruments mitigate the impact of transport and commuting on climate change by encouraging the reduction of greenhouse gas emissions in urban areas.

Given the peculiar nature of commuting, the network paradigm has often been adopted to study the patterns of habitual movements between origins and destinations. Following the dominant traditional approach to the study of commuting networks, many authors have applied spatial interaction models, which are modifications of gravity models (Johansson *et al.*

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2003; Patuelli *et al.* 2007; Thorsen and Gitlesen 1998). Spatial interaction models have also been applied to the study of other evolving spatial phenomena (Sen and Smith 1995).

Complex network analysis (CNA) has been used to study commuting networks. This approach is based on graph theory and was revamped at the turn of the last century (De Montis *et al.* 2007; Patuelli *et al.* 2007; Russo *et al.* 2007). One of the main features of CNA, compared to other traditional approaches (i.e. spatial interaction modeling), is that it aims at keeping the interactions among the elements of the systems at all possible hierarchical levels. In this way, the whole complexity of the interactions is stored in the network representation. By applying tools from graph theory, it is possible to characterize the global features of the system and to predict certain macro-scale properties of the multi-element system at a given degree of accuracy, by means of a limited number of variables and without modeling the characteristics of each individual element.

These statistical properties can be regarded as signatures of the emergence of the territorial phenomena that typify commuting in an insular setting. These phenomena affect the landscape and the distribution of land use as time passes. CNA techniques and software (after proper calibration and tuning) may be included in the toolbox of planners and policy makers to investigate these phenomena. Thus, complex network analysis—like other methods such as multi-criteria analysis and geographical information analysis—may become a useful part of a dedicated planning support system that is able to suggest strategies and actions suitable for specific classes of commuting systems.

Generally speaking, commuting systems can be characterized by defining the properties which they share in common with many other real-world phenomena. This approach provides new insights into the study of new classes of networks that behave differently from the common random graph networks. For example, small-world networks differ from random networks in that, while the diameter of the system scales very slowly with its size, the clustering coefficient of small-world networks is notably higher. Scale-free networks differ in that their connectivity distribution is much broader than it is in the random case, with divergent variance (see Section 2.1).

This paper presents an application of the graph-theory-based approach to the study of the inter-municipal commuting network of Sicily (Italy), the largest island in the Mediterranean. The authors start from the results obtained by De Montis *et al.* (2007) who studied the analogous commuting system of the island of Sardinia, Italy. We verify whether geographical similarities—consisting, in this case, in the fact that both study areas are islands—may result in the emergence of similar statistical properties.

The paper is developed as follows. The next section introduces the theoretical principles as well as the applications of CNA to spatial systems. Section 3 presents the main methodological aspects and the most relevant results obtained in the study of commuting behavior of Sardinia, as these prompted the authors to develop a similar study for the island of Sicily. The focus of Section 4 is on the Sicilian inter-Municipal Commuting Network (SiMCN): the authors analyze its topology, the traffic, and the interplay of these two factors. In Section 5, SiMCN is compared to the Sardinian commuting network. Section 6 presents overall conclusions and perspectives.

2 Complex network analysis (CNA): theoretical insights and applications

2.1 Theoretical principles

Network theory begins with the elaboration of graph theory by Euler.[1] This area of study was developed and expanded in the 1960s by Erdős and Rényi 1959; 1960. In seminal works, they studied the structure of random graphs, where each pair of nodes in the graph is linked with a probability p. In such cases, the probability distribution of the degree k of a node (the number of its connections with the nearest neighbors) takes the form of a bell curve and has a finite and characteristic mean value.

At the turn of the last century, the availability of ever-larger data sets and the parallel explosion of computer processing power allowed CNA to be systematically and intensively applied to the study of very large networks (Albert and Barabási 2002; Pastor-Satorras and Vespignani 2004). These networks have a very large number of nodes, N, when compared to the average degree value ($N \gg \langle k \rangle$).

The renewal of network theory started with the work of Watts and Strogatz (1998), who first proposed a simple network model to explain a well-known social spreading phenomenon called the small-world effect (Milgram 1967). In this network, social interaction is modeled by a regular one-dimensional lattice in which a random rewiring process is introduced in order to produce the small-world effect for which the average shortest path length between a pair of nodes scales very slowly with the number of nodes $N(l \sim \log N)$. Another important property, which has been found in many natural and technological networks, is that the probability distribution of the degree $P(k)$ does not provide any characteristic value in presence of a diverging measure of the statistical fluctuations (variance). In this case, scale-free behavior is found, due to a power law trend in the probability distribution of the degree k. These networks are said to be scale-free because they have invariant statistical properties over the entire range of degree values. The presence of heavy tails in the probability distribution curve is also often a sign of a non-negligible probability of encountering nodes with very large degree value—the "hubs" of these networks. A popular mechanism for explaining the growth of these special networks is "preferential attachment" (Barabási and Albert 1999): as new nodes are added to the network during the growth process, they tend to take the greatest advantage from the system they join by linking to nodes that have a very large degree value, i.e. the network hubs.

Recent developments in CNA focus on the analysis of a quantity—the "weight"—attributed to each edge (Barrat *et al.* 2004; Barthélemy *et al.* 2005). In these approaches, authors adopt a generalization of the series of measures developed to study the purely topological characteristics of networks. In addition, inspection of the probability distribution of the strength, the generalization of the degree k summing the weights attached to the edges converging to a given node, has often shown that a network exhibits scale-free behavior. Other relevant results have come from the analysis of the interplay between traffic and topology, which has led to the identification of super-proportional correlations indicating that the information/traffic properties of a complex network cannot be explained by topology alone.

[1] Applying graph theory for the first time in his "Solutio problematis ad geometriam situs pertinentis" (1736), the great mathematician demonstrated that it was impossible to complete a walking tour of the city of Königsberg by crossing each of its seven bridges only once (after Caldarelli 2007).

2.2 Empirical applications

CNA has been applied to both simulated and real systems. Apart from computer simulations, CNA provides insights into a wide range of issues such as food webs, human interactions, the Internet and the World Wide Web, the spread of diseases, population genetics, genomics, and proteomics. In each of these cases one starts by inspecting recurrent structures embedded in complex systems characterized by non-identical elements (the nodes) connected through different kinds of interactions (the edges). For a review of these applications, see Albert and Barabási (2002); Newman (2003).

Recently, in the many fields grouped under the general heading of "regional science," a number of scholars have begun using complex network analysis to model urban social and economic systems at the urban (Batty 2001, 2008; Jiang and Claramunt 2004) and regional (Latora and Marchiori 2003; Schintler *et al.* 2005) scales. Such network models can be seen as interlaced compositions of individual entities (the nodes) and their multiple interactions (the links). Many authors have attempted to extend the analysis beyond topology and traffic by examining the influence of geographical space on the properties of the network (Campagna *et al.* 2007; Crucitti *et al.* 2006; Gastner and Newman 2004; Gorman and Kulkarni 2004).

Some applications, which are of particular interest for this paper, refer to the study of infrastructures and commuter behavior Chowell *et al.* (2003); Guimera *et al.* (2003); Latora and Marchiori (2002); Sen *et al.* (2003). These works have often assumed that the emergence of scale-free properties indicates that the system behaved efficiently. Examples of this are the hub-and-spoke structure of transportation systems by O'Kelly (1998) and, in particular, that of airline networks by Reggiani *et al.* (2009). In these systems, a few hubs have a very large degree, behave as pivots for many smaller (with a smaller degree value) satellite nodes, and often act as bridges between disconnected regions.

Of very special interest are those works which have applied CNA to the study of commuting. Patuelli *et al.* (2007) analyzed the topology of the German commuting network. De Montis *et al.* (2007) used a weighted network approach to analyze inter-municipal commuting in the Italian region of Sardinia, the second largest island in the Mediterranean. In the next section, we report the main results of this analysis.

3 Properties of the Sardinian inter-Municipal Commuting Network

This study is based on the analyses of the inter-municipal commuting system of Sardinia, Italy by De Montis *et al.* (2007). In that study, the authors inspected the daily movements of workers and students by adopting a network representation: the Sardinian inter-Municipal Commuting Network (SMCN). This network had $N = 375$ vertices, each one corresponding to a town, and $E = 8124$ edges, each one representing the exchange of commuters between two towns.

The authors developed a number of measurements on this undirected graph, and on the corresponding representation, by giving each link a weight representing the number of commuters that flowed through that connection. This weighted, undirected network was actually built by processing information from the regional origin destination table, a dataset of the daily movements for work and study among Sardinian municipalities. Below we report the most important results of the study.

Topological analyzes show that the SMCN belongs to the class of random networks, since the probability distribution of degree k has a bell shape around a finite mean value. Study of the clustering coefficient shows a divergence from the usual random network behaviors and reveals properties common to other transportation networks, such as the world airline network (Barrat *et al.* 2004), the Indian Railway system (Sen *et al.* 2003), and the Boston subway (Latora and Marchiori 2002). To be more precise, small (with small k) municipalities are locally densely interconnected, while large municipalities (even hubs of the network) provide a large set of connections for remote regions which are otherwise disconnected.

Weighted network analysis showed that the complementary cumulative probability distribution of both weights and strengths (total commuter traffic handled by the municipalities) had a power-law regime with a wide spectrum of degree values. No characteristic distribution value was found in this case, and the SMCN can be included in the class of scale-free weighted networks.

Analysis of the interplay between demographic, traffic, and topological properties showed that the spectrum of the strength averaged over the values of the degrees exhibited super-linear behavior. This finding implies that the higher the number of connections to a town, the larger the traffic per connection handled. This makes it most likely there are hidden properties that control and describe the behavior of the network.

4 Examining the Sicilian inter-Municipal Commuting Network

In the previous section, the properties of the SMCN were described. In this section similar network analyzes are used to examine the topological and traffic characteristics of the Sicilian inter-Municipal Commuting Network (SiMCN).

4.1 Setting the case study and dataset

Sicily, an administrative region of Italy, is the largest Mediterranean island and is divided from the mainland by the strait of Messina, which is three kilometers wide at its narrowest.

A broad description of Sicilian commuter behaviors is provided by the Origin-Destination Table (ODT), a census dataset that describes the movements for work and study of inhabitants from their homes to the usual destinations (Istat 1991). Commuters' movements are also described with reference to time of travel and means of transportation. Using the model of De Montis *et al.* (2007), the ODT is the main source of information for constructing the adjacency matrix $\mathbf{A}$, the standard mathematical representation of a network, whose general term a_{ij} is equal to 1, if at least one person commutes from the origin town i to the destination town j, and is otherwise equal to zero. In this case, $\mathbf{A}$ has null diagonal elements ($a_{ii} = 0$), since movements of commuters within the same municipality are not considered. The adjacency matrix $\mathbf{A}$ describes the mutual relationships between each pair of municipalities, and these are plotted in Figure 2 in a spatial representation of the SiMCN.

In this analysis, commuters' movements are investigated irrespective of the means of transportation.

Even though Sicilian geography would suggest extending analysis of the commuter network to the mainland city of Reggio Calabria, this work focuses only on commuter movements

Figure 1: A general view of Italy. The islands of Sardinia and Sicily are shaded in dark gray.

between Sicilian municipalities. This is because Reggio Calabria contributes only 1247 commuters to the traffic of SiMCN and is thus negligible in terms of total traffic.

4.2 Topology of the SiMCN: analysis and interpretation

As indicated in the previous section, the system of commuter movements among Sicilian municipalities will be analyzed as a network, with a focus first on its topological properties.

The SiMCN has $N = 391$ nodes, which correspond to the set of Sicilian municipalities, and $E = 9993$ edges, which correspond to the pattern of commuter exchanges among those towns.

The first topological measure adopted in this study is the degree k of a given node i, which measures the number of nodes that are connected to it by one edge and is expressed as

$$k_i = \sum_{j \in V(i)} a_{ij} \tag{1}$$

where a_{ij} is an element of the adjacency matrix $\mathbf{A}$ and $V(i)$ denotes the set of neighbors of i.

Analysis of the probability distribution of the degree k provides a proxy indication of the centrality of the nodes, in terms of number of first neighbors connected to each node. Table 1 ranks the ten most "central" Sicilian towns. The most important administrative, financial and productive towns of the island—Palermo and Catania—are at the top.

Analysis of the probability distribution of the degree $P(k)$ of the nodes (Figure 3) reveals the emergence of a log-normal behavior with a fast-decaying tail and a characteristic mean value at $\langle k \rangle = 51$, while the maximum value of k is 280. These general properties of the probability distribution $P(k)$ are a sign that the SiMCN has a random graph behavior. The low values of

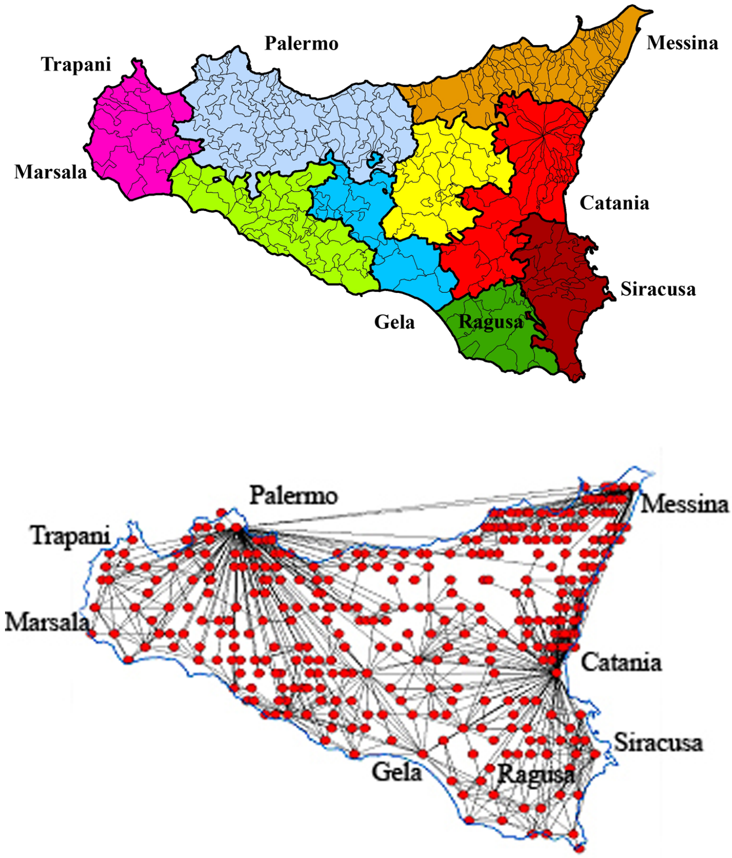

Figure 2: Top, administrative representation of Sicilian provinces and municipalities; bottom, spatial representation of the topology of SiMCN: the nodes (red points) represent the municipalities and the connecting lines a flow value larger than 50 commuters.

the average ($\langle l \rangle = 1.98$) and maximum ($l_{\text{max}} = 4$) path length between any pair of nodes indicates that the SiMCN has a small-world structure.

The application of the concept of path length in this context requires an explanation. In spatial analysis, the concept of path is connected to the (one-way) movement of agents—pedestrians, shoppers, random walkers, and the like—while its length is usually measured in terms of the number of steps required to reach one point from another. In complex network theory, path length is defined as the number of edges between two nodes. It is usually a generalization of the concept of path length measured in space, as it can be conceived of as an index of separation—generalized distance—between those nodes. Commuting is a phenomenon characterized by regular two-way movements: commuters travel to their destinations and go back to their homes. In the undirected graph representation adopted in this paper, edges correspond to the commuting relationships (two-way displacements) between each pair of towns. The path length—i.e., the number of edges dividing each pair of municipalities—has to be interpreted as a measure of the commuting separation between them. A path length equal to one denotes a first order (direct) commuting relationship; a path length equal to three indicates the existence of either three direct commuting relationships or, alternatively, a third-order (indirect) com-

Table 1: Ranking of Sicilian municipalities by degree.

Rank	Municipal centers	Degree k
1	Palermo	280
2	Catania	228
3	Messina	220
4	Caltanisetta	154
5	Enna	132
6	Termini Immerese	132
7	Bagheria	123
8	Giarre	122
9	Gela	120
10	Milazzo	119

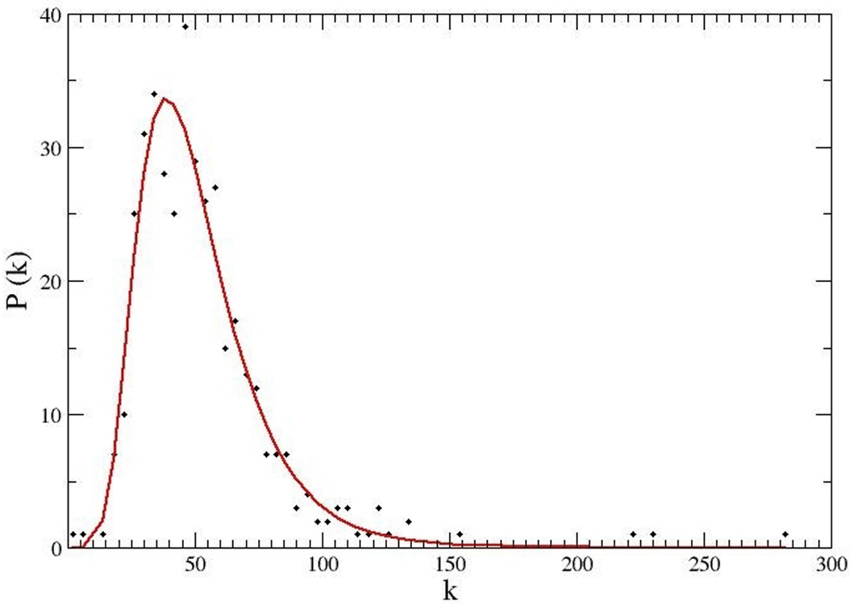

Figure 3: Plot of the probability distribution of the degree k for the SiMCN. The red line is a log-normal fit. This behavior signals the emergence of a random graph structure.

muting relationship between two municipalities. As in social networks, path length measures the level of logical distance between towns in terms of labor- or study-led activities, without direct reference to the physical distance, measured along the path actually adopted for displacement.

Another relevant quantity is the clustering coefficient, a measure of the level of local cohesiveness of a node. This obeys the following relationship:

$$C(i) = \frac{2E(i)}{k_i(k_i - 1)} \tag{2}$$

where $E(i)$ is the number of links between the k_i neighbors of the node i and $k_i(k_i-1)/2$ is the maximum number of possible interconnections among the neighbors of the node. The clustering coefficient ranges in the interval $[0, 1]$. Values close to 1 are a sign of very high local connectedness around a node, while the opposite is true for values approaching zero.

It is often preferable to consider an average of the clustering coefficient $C(i)$ for all nodes with a given k value. This is done by managing the following spectrum of the clustering coefficient versus the degree:

$$C(k) = \frac{1}{NP(k)} \sum_{i/k_i=k} C(i) \tag{3}$$

where $NP(k)$ is the total number of nodes of degree k. Figure 4 shows a downward sloping trend of $C(k)$ over the whole range of degree values.

This is a sign of the following property of transportation systems: the hubs of this network have first-neighbor nodes that generally are not connected each other, while small-degree nodes' nearest neighbors are much more interconnected. This implies that, at the topological level, large hub towns are linked to many satellite towns that are disconnected from each other, while small towns have fewer neighbors—but, by contrast, these are very often connected to each other. This pattern can be explained by the search for efficiency across the network as a whole: commuters often prefer to move from satellite centers to hub towns, seeking the higher level of services provided in the main towns.

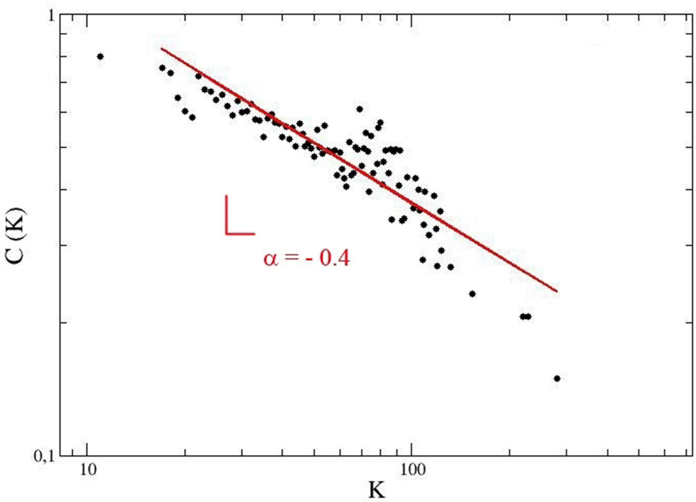

Figure 4: Log-log plot of the clustering coefficient versus the degree k for the SiMCN. Downward-sloping behavior, common in many transportation systems, can be detected.

4.3 Weighted network approach to the SiMCN: analysis and interpretation

The dataset adopted for this investigation, the Origin-Destination Table (ODT), provides information on the number of commuters that choose to move habitually from their home towns to other destinations. This information can be used as a basis for constructing the weighted adjacency matrix $\mathbf{W}$ of the SiMCN, where a generic element w_{ij} is equal to the sum of the number of commuters moving from the town i to the town j and vice versa, and a generic diagonal element w_{ii} is equal to zero. In this case, the symmetric weighted adjacency matrix $\mathbf{W}$ stands as the standard mathematical representation of the SiMCN, now conceived of as an undirected weighted network. $\mathbf{W}$ is structured as a symmetric matrix, using the framework proposed by De Montis *et al.* (2007), which has the advantage of characterizing a non-oriented "business relationship" between each pair of municipalities through a single value: the number of commuters exchanged daily.

Analysis of the complementary cumulative probability distribution of the weight $P(w)$ reveals that the values are highly heterogeneous: $w_{\max}$ is 10 233, three orders higher than its average value of $\langle w \rangle = 37.6$. Figure 5 shows the trend of the complementary cumulative probability distribution of the weight, which reveals power-law behavior over a wide range of weight values ($P(w) \approx w^{-\beta}$, with exponent $\beta = 2.0$). The relevant statistics confirm that the curve fits very well with a straight line ($R^2 = 0.96$, Tstat = 56.86).

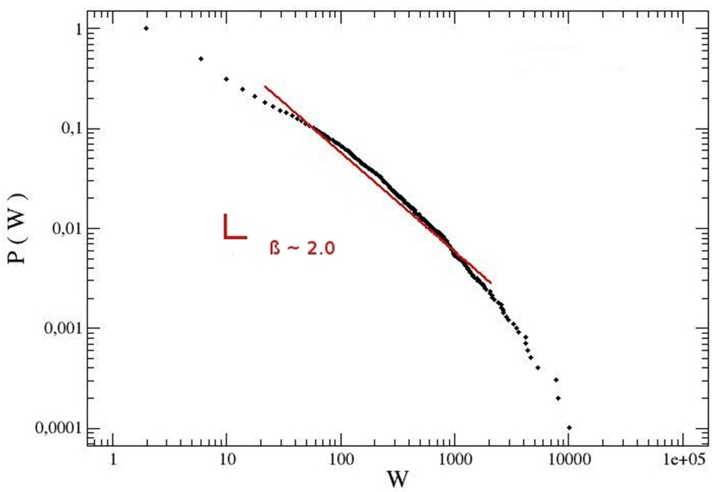

Figure 5: Log-log plot of the complementary cumulative probability distribution of the weights. A power law regime emerges over a wide range of w values with a slope exponent equal to 2.0.

The distribution of the weights characterizes the SiMCN, since the relevant connections can be analyzed among the main towns of the island. In Table 2, the five most important inter-municipal "dorsal links" are ranked by their correspondent weight.

Table 2: The five highest-ranked connections between municipalities in the SiMCN, according to their weights.

Rank	Pairs of connected municipal centers	Weight w
1	Misterbianco - Catania	10233
2	Erice - Trapani	8127
3	Gravina Di Catania - Trapani	7857
4	Tremestri Etneo - Trapani	5400
5	Trapani - Aci Castello	4724

In this weighted network approach to the analysis of the SiMCN, it is useful to adopt a generalization of the topology centrality measure. The strength s is defined as the sum of the weights corresponding to the edges connected to a given node i. The strength is defined as

$$s_i = \sum_{j \in H(i)} w_{ij} \tag{4}$$

where w_{ij} is an element of the weighted adjacency matrix $\mathbf{W}$.

The strength offers another proxy indication of the centrality of a node in a network. In this case the strength can be interpreted as a measure of the capacity of a town to exchange commuters from nearest neighbor municipalities. Table 3 ranks the ten "busiest" towns.

Table 3: Ranking of municipalities in the SiMCN by their strength.

Rank	Municipalities	Strength s
1	Catania	80326
2	Palermo	49500
3	Siracusa	17800
4	Messina	16987
5	Trapani	16578
6	Misterbianco	13801
7	Agrigento	13323
8	Gravina di Catania	10644
9	Erice	9794
10	San Giovanni La Punta	9099

Figure 6 shows the trend of the complementary cumulative probability distribution of strength $P(s)$; notable features include the power law behavior ($P(s) \approx s^{-\beta}$, with exponent β = 2.0) and the heavy tail of the curve, which are signs that the SiMCN includes a non-negligible number of hubs when it is seen as a weighted network. In this case there is no characteristic value for the probability distribution and the slope exponent is a quantitative indication of the level of heterogeneity in the system. Once again the curve fits very well to a straight line (R^2 = 0.85, Tstat = 40.48).

These results open up a novel perspective of the analysis which has been developed up to this point. While the SiMCN can be classified, purely topologically, as a random network, analysis of commuter flows suggest that it belongs to the class of weighted scale-free networks.

4.4 An analysis of the interplay between traffic and topology

This section analyzes the interplay between the traffic and topological properties of the SiMCN. Considering the functional relationships between weighted and topological centrality of the Sicilian towns allows us to determine how the measure of the total amount of commuters exchanged in a single municipality (vertex) scales with respect to the number of towns within a one-hop district. In other words, it also enables traffic per connection of each town to be monitored. In the present case, this study investigates the relationship between strength s and degree k. Figure 7 shows the spectrum of the average values of s for each degree k of the nodes.

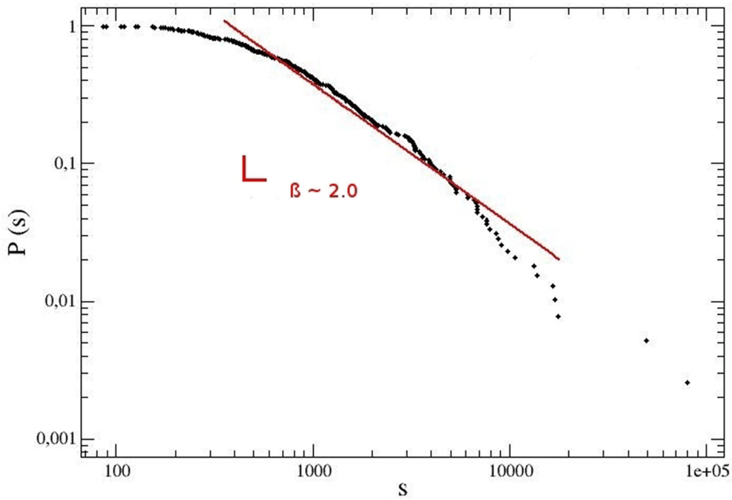

Figure 6: Log-log plot of the complementary cumulative probability distribution of the strength $P(s)$. The line fits a power law trend with slope exponent equal to 2.0.

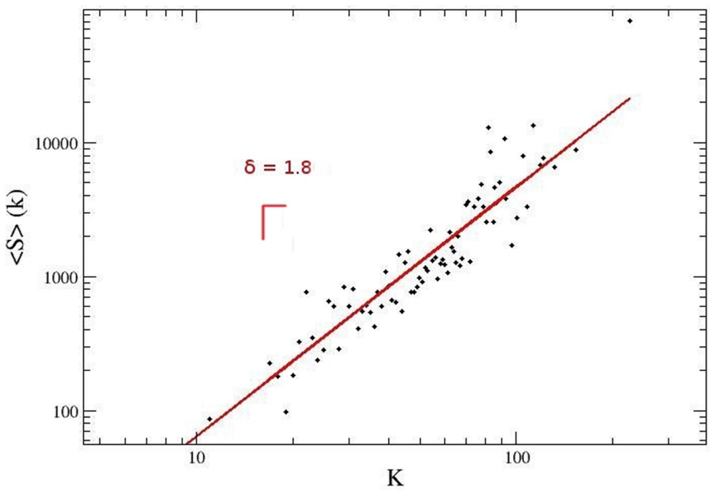

Figure 7: Log-log plot of the spectrum of the strength s versus the degree k. A super-linear correlation is evident, with a slope exponent $\delta = 1.8$.

Table 4: Comparative overview of topologies of the SMCN and SiMCN.

	N	E	$k_{\min}$	$k_{\max}$	$\langle k \rangle$	$\langle l \rangle$	$l_{\max}$
SMCN	375	8124	8	279	40	2.0	3
SiMCN	391	9993	1	280	51	1.98	4

A positive correlation exists between these two values, and a power law regime is evident over the whole range of degree values ($s(k) \approx k^{\delta}$, with exponent $\delta = 1.8$). The relevant statistics confirm that the curve fits very well to a straight line ($R^2 = 0.93$, Tstat = 28.26).

This implies that the strength s of a given node, on average, almost scales with the square of its degree k: the higher the degree of a node (the higher its number of first-neighbor towns), the higher (super-proportionally) the strength (corresponding to the total amount of commuter traffic handled). This evidence confirms similar results from the Sardinian inter-Municipal Commuting Network (SMCN). In both cases, the traffic per connection increases when the number of connections (degree k) increases; this super-linear behaviors suggests that there are some hidden economies of scale.

5 Discussion: Comparing the SMCN and the SiMCN

The preceding section analyzed the Sicilian commuting network (SiMCN) and reported its most relevant statistical properties. A brief interpretation of the results was also proposed, as it is possible to detect the emerging phenomena that characterize that particular commuting system. Similar phenomena were also found in many cases to characterize the corresponding Sardinian commuting network (SMCN).

In order to examine in more detail the similarities of the Sardinian and Sicilian commuting networks, in this section we construct and comment on a synthetic framework.

The topological properties summarized in Tables 4 and 5 show that both systems can be classified as random networks with natural small-world properties. This is because they have very low average path length values $\langle l \rangle$ (the generalized index of separation between pairs of municipalities, as defined in Section 4.2) when compared to the number of nodes. This finding implies that information is able to flow very efficiently in these networks. Sicily has, on average, a higher local cohesiveness (twice as large), as shown by the value of $\langle C \rangle$, confirming that there are more commuter relationships between Sicilian towns of a similar size (with a similar degree) at the local level; in Sardinia, on the other hand, small towns are more likely to exchange commuters with hub towns in a star-like or core-periphery pattern.

The probability distribution of degree $P(k)$ has a bell shape for both Sardinia and Sicily, with a characteristic and defined mean value. This leads us to conclude that those networks belong to the class of random graphs. The spectrum of the clustering coefficient with respect to degree is similar in the commuting networks of both islands. Hub towns tend to connect otherwise disconnected regions, while towns with small degree k are very densely connected locally. This is particularly evident for the SMCN, with an average clustering coefficient of 0.26, which is a sign of a core-periphery pattern in the local structure of commuting. In the SiMCN, by contrast, the higher value of $\langle C \rangle$ (equal to 0.52) is a clear sign of the rise of a number of

Table 5: Comparative overview of the topology of the SMCN and SiMCN, part 2.

	$P(k)$	$C(k)$	$\langle C \rangle$
SMCN	Random graph structure	Downward sloping	0.26
SiMCN	Random graph structure	Downward sloping	0.52

Table 6: Comparative overview of the traffic properties of the SMCN and the SiMCN.

	$\langle w \rangle$	w_{max}	$P(w)$
SMCN	27	13953	Power law with exp 1.8
SiMCN	37.6	10233	Power law with exp 2.0

commuting relationships between pairs of peer level towns, in a sort of periphery-periphery pattern.

With respect to the traffic properties outlined in Tables 6 and 7, the weights in both cases are quite heterogeneous and the complementary cumulative probability distribution $P(w)$ exhibits power law behavior. The behavior of the complementary cumulative probability distribution of the strength s clearly fits a power law line, with a slope exponent close to 2 in both the SMCN and the SiMCN. In this sense those systems can be classified as scale-free weighted networks.

Analysis of the interplay between traffic and topology shows once again that there are similarities between the SMCN and the SiMCN. In both cases there is super-linear behavior in the spectrum of the strength with respect to the degree k. In both networks, the traffic per connection increases when the degree k increases. In other words, the greater the topological centrality of a town, the greater its centrality for traffic.

6 Conclusions and perspectives

In this paper the authors have developed a framework for weighted network modeling of the commuting system of Sicily, Italy, comparing it with an earlier analysis of the corresponding system in Sardinia.

As a preliminary result, it is possible to state that the Sardinian and the Sicilian intermunicipal commuting networks are statistically similar in their general and local properties. From these results, one can infer that in similar geographical settings (in this case, two islands with comparable geographic features) similar commuting networks emerge. Given the generally accepted assumption among scholars (Albert and Barabási 2002) that similar properties

Table 7: Comparative overview of the traffic properties of the SMCN and the SiMCN, part 2.

	$P(s)$	$\langle s \rangle(k)$
SMCN	Power law with exp 2.0	Upward sloping with exp 1.9
SiMCN	Power law with exp 2.0	Upward sloping with exp 1.8

may be detected even in completely different settings, the authors are well aware that their hypothesis needs to be checked by studying other dissimilar regional systems; thus, they will direct future research efforts to the following issues:

1. an inspection of the evolution of commuter networks in non-island regions, such as Lombardy, in Northern Italy, and Umbria, in central Italy;
2. analysis of commuter networks in other European nations and regions;
3. the development of the same approach at different spatial scales, starting from the study of the whole Italian commuter network: it is worth checking whether or not the same properties can be observed at a larger than regional scale.

The methodology used in this paper is based on adopting and developing network analysis, a technique which can help uncover complex phenomena by using a limited set of variables that show the collective features of commuting systems. They also envisage incorporating network analysis into the toolbox of professional planners and decision makers who have to tackle those complex commuter issues which have an impact on the landscape and land use in the Italian islands.

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