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Research Article

Spanish Airport Network Structure: Topological Characterization

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Applied complex network theory has become an interesting research field in the last years. Many papers have appeared on this subject dealing with the topological description of real transport systems, from small networks like the Italian airport network to the worldwide air transportation network. A comprehensive topological description of those critical structures is relevant in order to understand their dynamics, capacities, and vulnerabilities. In this work, for the first time, we describe the Spanish airport network (SAN) as a complex network. Nodes are airports, and links are flight connections weighed by traffic flow. We study its topological features and traffic dynamics. Our analysis shows that SAN has complex dynamics similar to small-size air transportation networks of other developed economies. It shares properties of small-world and scale-free networks, and it is highly connected and efficient and has a disassortative pattern for high-degree nodes.

1. Introduction

The ideas and methods of modern complex networks appeared for the first time in the 1920s in the context of educational and developmental psychology [1]. Since then, network theory has become a popular research subject and has been applied to many scientific fields: computer networks and the Internet, technological networks, social networks, economic networks, biological networks, or transport systems [2, 3].

Complex network analysis has been widely applied to the analysis of topology and traffic dynamic of transport systems like subways [4], railways [5], public transportation [6], or air transportation networks.

Transport systems are critical infrastructures with economic and social impact in our society. A good knowledge of the network structure is crucial for making efficient and rational decisions about logistics, sustainability, or mobility in this context.

Topology features of transport networks like centrality, presence of hubs, and critical nodes are of application for protecting the network against failures or attacks. Traffic flow description, network robustness, vulnerability, or weaknesses are other relevant features of transport systems which can be analyzed by complex network methods.

In this work, we are focused on air transport systems. Airport networks are modeled by weighted graphs $G=(V, E, W(G))$ [7–9], where V is the set of airports, E is the set of direct connections between them, and $W(G)$ is the weight matrix. Weighted links can measure different characteristics of connectivity, like traffic flow (real passengers or freight traffic) between airports or economic costs like geographical distances, flight times, or fuel consumption.

If we are only interested in topological structure of the network, then we denote $A(G)$ as the binary adjacency matrix of the graph.

This work deals with routes, passenger traffic, and geographical distances; thus, we assume that if there exists a direct flight from airport i to airport j, also a flight from j to i is scheduled and both have similar traffic, frequency, and length. Then, we consider only undirected graphs.

This mathematical description has been applied last years to deal with topological description of air systems (China [10–13], India [14], US [15], Brazil [16], Australia [17, 18], Italy [19], Turkey [20], Europe-China-US [21], and the world airport network (WAN) [22–25]).

Topological features of networks are invariant of their underlying graphs. Some of them can be used to determine common properties of real networks like *small-world networks* [26, 27] and *scale-free networks* [28]. This characterization is well known in the literature.

In this paper, we analyze and describe the Spanish domestic airport structure as a complex network. Data contains direct flights between network airports, their traffic flow as a measure of importance of routes and airports, and geographical distances.

This paper is organized as follows. The first section contains a brief summary of topological features of networks we have considered in this work. Next sections describe the Spanish airport network (SAN) database and provide a detailed exposition of its topological characteristics. Finally, we conclude this work with a summary and discussion of our analysis.

2. Network Structural Measures and Models

2.1. Structural Metrics. A network is represented by a graph $G=(V,E)$, where V is the nonempty set of nodes and $E \subset V \times V$ is the edge set. We denote by $n=|V|$ the number of nodes and by $m=|E|$ the number of edges of network G. In our case of study, nodes represent airports in the SAN; they are denoted indistinctly by v_i or i in this paper. Edges $(v_i, v_j)=(v_j, v_i)$ represent regular routes between nodes. Graph density $d=2m/n(n-1)$ is the ratio of the number of edges and the number of potential edges.

The information about connections is stored into the adjacency matrix $A(G)=(a_{ij})$ whose rows and columns are labeled by graph vertices. If weight values are considered, then the weight matrix $W(G)$ adds weight information w_{ij} in each position (i,j).

Since our network SAN collects airports and commercial routes, then the associated graph (or weighted graph) contains no loops.

The following sections briefly describe the structural metrics used in this work to characterize the SAN. These structural metrics are gathered in three categories: degree- and weight-based measures, clustering measures, and centrality measures. Tables 1 and 2 include notations and formulas [2, 29, 30].

2.1.1. Degree- and Weight-Based Measures. Node degree k_i and average degree $<k>$. Parameter k_i measures the total number of connections or neighbors a node i has. High-degree nodes are known as *hubs* and correspond in our case to central airports having connections to many others. Average degree $<k>$ is the average of node connections in the network.

Node strength s_i. The notion of degree is generalized to weighted networks by the notion of strength: the strenght of a node is the sum of weights of links connected to the given node instead of the number of edges. High-strength nodes correspond to airports with high passenger traffic or airports connected to many peripheral cities.

Degree distribution $p(k)$ and $p(>k)$. Let $p(k)$ denote the probability that a random node has degree k. This function is usually referred to as degree distribution. The probability of a random node has degree higher than k, and $p(>k)$ is the accumulated version.

Average nearest neighbor degree of node $ik_{nn,i}$. Degree distribution completely determines the statistical properties of uncorrelated networks. Nevertheless, most real networks, like transport networks, are correlated, and the probability of

Table 1: Structural measures of unweighted networks and notations.

Symbol	Metric	Equations
n	Number of nodes	—
m	Number of links	$\sum \frac{a_{ij}}{2}$
d	Density	$\frac{2m}{n(n-1)}$
$V(i)$	First connections of node i	—
k_i	Node degree of node i	$\sum_j a_{ij}$
V_k	Set of k-degree nodes	—
$n(k)$	Number of k-degree nodes	—
$\langle k \rangle$	Average degree	$\sum_i (k_i/N)$
$p(k)$	Degree distribution	$\left\lvert \frac{V_k}{n} \right\rvert$
$p(>k)$	Cumulative degree distribution	$\sum_{k'>k} p(k')$
$K_{nn,i}$	Average nearest neighbor degree of node i	$\sum_{j \in V(i)} \frac{k_j}{k_i}$
$K_{nn}(k)$	Average degree of nearest neighbors of k-degree nodes	$\sum_{k_i=k} K_{nn,i}$
r	Degree correlation	NA
C_i	Clustering coefficient of node i	$\sum \frac{a_{ij}a_{jk}a_{ki}}{k_i(k_i-1)}$
C	Clustering coefficient	$\sum \frac{C_i}{n}$
$C(k)$	Clustering coefficient of k-degree nodes	$\sum_{i \in V_k} (C_i/n(k))$
d_{ij}	Shortest path length from i to j	NA
D	Diameter	$\max d_{ij}$
L	Average shortest path length	$\sum_{i=j} (d_{ij}/n(n-1))$
E	Efficiency	$\sum_{i=j} \frac{(1/d_{ij})}{n(n-1)}$
D_i	Damage of node i	$(E-E_i)/E$
$C_B(i)$	Betweenness centrality of node i	$\sum_{j=l} \frac{\sigma_{jl}(i)}{\sigma_{jl}}$
$C_C(i)$	Closeness centrality of node i	$\frac{1}{\sum_j d_{ij}}$
$C_E(i)$	Eigenvector centrality of node i	NA

Table 2: Structural measures. Weighted networks.

Symbol	Metric	Equations
s_i	Node strength	$\sum_j w_{ij}$
$K^w_{nn,i}$	Average weighted nearest neighbor degree of node i	$\sum_{j\in V(i)} \frac{w_{ij}k_j}{s_i}$
$K^w_{nn}(k)$	Average weighted degree of nearest neighbors of k-degree nodes	$\sum_{k_i=k} K^w_{nn,i}$
d^w_{ij}	Shortest path length from i to j	NA
D^w	Diameter	$\max d^w_{ij}$
L^w	Average shortest path length	$\sum_{i=j}\left(d^w_{ij}/n(n-1)\right)$
C^w_i	Clustering coefficient of node i	$\sum \frac{(w_{ij}+w_{ik})a_{ij}a_{jk}a_{ki}}{2s_ik_i(k_i-1)}$
C^w	Clustering coefficient	$\sum \frac{C_i}{N}$

a k-degree node is connected to a k'-degree node $p(k' \mid k)$ depending on k. To deal with this idea, the average nearest neighbor degree of node $ik_{nn,i}$ computes the mean degree of the neighbor set $V(i)$ of a node i.

Average degree of the nearest neighbors of k-degree nodes $k_{nn}(k)$. Denote V_k as the set of k-degree nodes. $k_{nn}(k)$ is the sum of $k_{nn,i}$ for all k-degree nodes $v_i \in V_k$. This metric can also be expressed as follows:

$$k_{nn}(k) = \sum_{k'} k' P\left(k' \mid k\right). \quad (1)$$

Note that $k_{nn}(k)$ does not depend on k for uncorrelated networks. On the other hand, if $k_{nn}(k)$ is an increasing function of k, it is said that network has a *assortative behaviour*, whereas if $k_{nn}(k)$ is a decreasing function of k, it is said to have a *disassortative behaviour*. Thus, in an assortative airport network, cities are more likely connected to others with a similar degree while in a disassortative airport network, high connected nodes tend to be connected to low connected airports.

Degree correlation r. When an assortative or disassortative behaviour is observed, the correlation between degrees can be quantified by the Pearson correlation coefficient r of pairs (k_i, k_j) for all edges $(v_i, v_j) \in E$. Thus, r is positive for assortative networks, and disassortative networks have negative degree correlation r.

Average weighted nearest neighbor degree of node $ik^w_{nn,i}$. This metric is the weighted analogous of the above metric $k_{nn,i.}$

Average degree of nearest neighbors of k-degree nodes $k^w_{nn}(k)$. This metric is the weighted version of metric $k_{nn}(k)$.

2.1.2. Clustering. Clustering coefficient C_i and C^w_i. (v_i, v_j, v_k) is a clique or triple if it forms a complete subgraph (a connected triangle) of the network. Clustering coefficient of node i quantifies how likely two first connections j, k of node i are linked in the network, being a triple, and it is computed by the ratio of the triples containing node i and all possible links between its neighbors. It is also known as *transitivity*. Airports with a high clustering coefficient are more interconnected than lower ones. Its weighted version C^w_i is a generalization of this metric to weighted networks.

Average clustering coefficient C and C^w. Average of all C_i coefficients in the network. It quantifies the local connectivity and transitivity of the airport network as a whole.

Clustering coefficient of k-degree nodes $C(k)$ and $C^w(k)$. Average of all clustering coefficients C_i or C^w_i, respectively, of all nodes of V_k.

2.1.3. Distance-Based Metrics. In this section, metrics are related to optimization problems; thus, weights are supposed to be "cost" values, geographical or orthodromic distances, fuel consumption, flight ticket prices, etc.

Shortest path length from i to jd_{ij} and d^w_{ij}. d_{ij} is the length of the geodesic between nodes i, j. We consider only connected networks, and the shortest paths are finite therefore. In the context of airport networks, d_{ij} is the number of flights to travel between airports i, j. If we consider weights on edges as geographical distances, we are interested in the shortest paths with respect to the sum of the weights of edges on a path, i.e., the total distance from i to j, and denote $d^w_{i,j}$ as the minimal sum.

Average shortest path length L and L^w. Mean of geodesic lengths over all pairs (i, j) and unweighted and weighted versions. They are well-known measures of the separation between nodes and play important roles in transport problems. If the transport network is disconnected, then only pairs belonging to the largest connected component are considered. All real air transport networks mentioned in this paper are connected.

Diameter D. Maximum value of d_{ij} (maximum number of flights to travel between two cities travelling trough a geodesic).

Efficiency E. Harmonic mean of geodesic lengths. It quantifies the traffic capacity of a network. $E = 1$ for completed graphs and $E = 0$ if V is a set of isolated nodes $(E = \varnothing)$.

Node damage D_i. Relative decrease in efficiency after removal of node i. It quantifies the resilience to node removal in the network. Consequently, the more damage an airport has, the more important is its theoretical interruption in case of failures, catastrophes, attacks, or other potential threats.

2.1.4. Centrality. Node betweenness centrality $C_B(i)$. It quantifies the importance of a node with respect to its centrality as a communication bridge. Firstly, the rates of geodesics going through node i $(\sigma_{jl}(i))$ and the total number of the shortest paths connecting nodes j, l (σ_{jl}) are computed for all pairs (v_j, v_l). Betweeness centrality is the sum of all possible rates. A node with high value of betweenness has the capacity to control a significant part of the flow of traffic in the airport network due to the fact that there are many nodes communicated through it.

Table 3: Comparative of some basic airport metrics and structure. The last row contains the corresponding topological measures of a random network generated with the RE(n, p) model sharing n and m with SAN.

Year	Authors	Network	n	$\langle k \rangle$	d	L	C	Structure
2005	Guimerà et al.	WAN	3883	13.93	0.004	4.4	0.62	SF SW
2007	Guida el al.	Italy	42	12.4	0.302	1.98/2.14	NA	SF SW
2008	Bagler	India	79	11.52	1.148	2.26	0.66	SF SW
2008	Xu et al.	US	272	48.28	0.178	1.84/1.93	0.73/0.78	SF SW
2011	Wang	China	144	14.14	0.099	2.23	0.69	SW
2017	Hossain et al.	Australia	131	9.10	0.069	2.9	0.5	SF SW
2020	This study	Spain	40	11.8	0.303	1.76	0.73	SF SW
—	—	RE ($n = 40$, $m = 236$)	40	11.8	0.303	1.49	0.295	Random

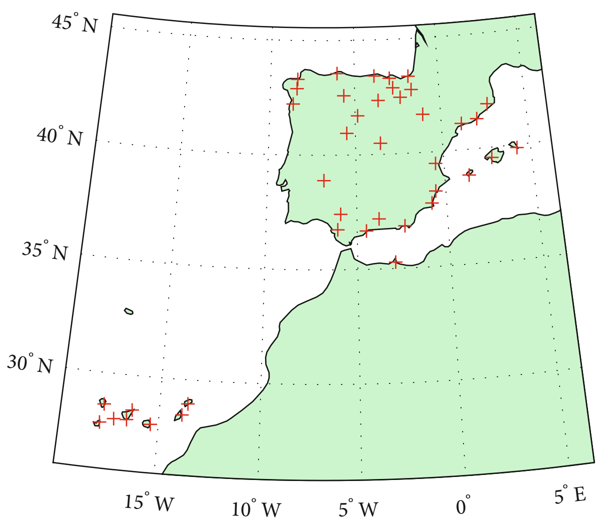

Figure 1: The Spanish airport network (SAN). Spatial distribution.

Node closeness centrality $C_C(i)$. Inverse of the sum of the shortest path length from node i to the other nodes in the network. A node with high closeness is an important communication node, related to efficiency and minimal cost in communication, due to its proximity to other nodes in the network.

Eigenvector centrality $C_E(i)$. It quantifies not only the number of neighbors a node has but also the quality of its connections. Connections to cities which are themselves hubs will lend a city more central than connections to less influential cities [31].

2.2. Topological Properties of Real Networks. Below, we briefly report some of the most relevant classes of networks related to our case of study.

Random network and Erdös and Rényi model (ER): Erdös and Rényi firstly proposed a model to generate graphs with random connections between nodes in the 1950s [32–34]. The procedure to generate ER networks starts with n disconnected nodes which are randomly linked with probability p until a fixed number of connections are reached. These graphs are uncorrelated; hence, their connections are independent of degree k; that is to say, $p(k' \mid k)$ and $k_{nn}(k)$ do not depend on k. Other topological properties of ER random graphs are the following: they typically have short path length L, they have also small clustering coefficient $C = <k>/n$, and their degree distribution is a Poisson distribution. Nevertheless, the ER random model does not adequately reproduce most of the properties or real complex networks [27].

Small-world network (SW): many real networks exhibit the "small-world property": any two nodes are connected by a relatively short path. Watts and Strogatz [26] defined SW networks as those having large clustering coefficient C, much higher than random networks, and short path length L. They proposed the SW model based on randomly replacing a fraction of the links of a n-node ring with new random links [27, 30]. Many papers have examined SW properties of air transport systems (see Table 3).

Scale-free (SF) network: Barabasi and Albert [28] described scale-free networks like SW networks whose new nodes preferentially connect to higher-degree existing nodes. This is called the "preferential attachment property". SF networks also present the property of having power law degree distributions.

3. The Spanish Airport Network (SAN)

Data for this work have been obtained from the OAG database web page (OAG Analyzer). Database contains information of flights with departures or arrivals to Spanish airports during 2015.

The air transport system is a strategic sector. Domestic and international air passenger traffic had decreased during the economic crisis but significantly recovered in 2015. This mobility growth trend started in 2013 in Spain. In fact, Spanish Transportation and Logistics Observatory (OTLE) reported a total number of 31,076,530 passengers travelling between Spanish airports during 2015.

The database analyzed in this paper contains information of direct flight reservations between each pair of airports in the network; thus, we only have considered domestic flights. As we pointed above, passenger traffic has suffered fluctuations in recent years; nevertheless, the route structure of national passenger air transport of Spain has remained similar from 2015 nowadays. To be concrete,

(i) each airport is taken as a node v_i

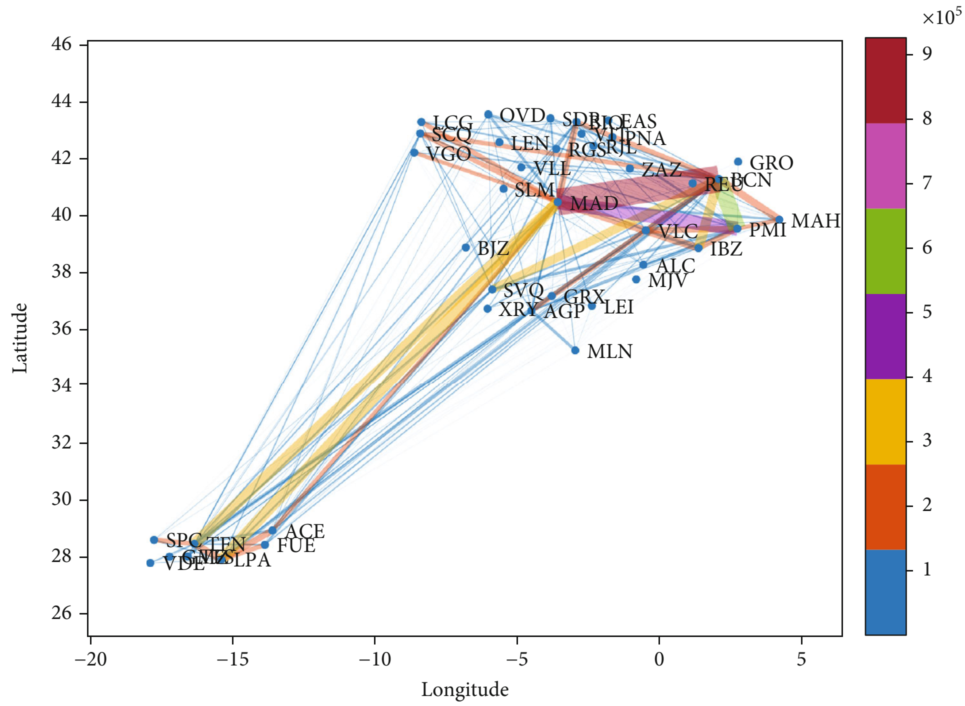

Figure 2: SAN weighted by passenger traffic. Edge width is proportional to the number of reservations (maximum of outbound and inbound flight). Airports are labeled by their corresponding IATA code.

(ii) links correspond to regular air routes between nodes in the network; thus, international flights are not considered

(iii) two airports connected with an outbound flight are supposed to be connected with the corresponding inbound flight, and the negligible difference between passengers' flow of bidirectional flights connecting two nodes is not considered; therefore, SAN is modeled by an undirected graph

(iv) if we only take into account whether a regular route between two airports had traffic in 2015 or not, SAN is modeled by an unweighted graph

(v) in other cases, we analyze weighted SAN by considering two possibilities:

   (a) Airport traffic measured by the maximum in-out number of reservations in each route. We use this information to understand properties related to the importance of nodes considering passenger flow

   (b) Orthodromic distance-shortest path lengths on the surface of earth-between airports. This weighted network is considered for cost-based properties (shortest path lengths and related metrics).

There were 48 airports in the Spanish airport network by 2015 according to the information provided by AENA. Since we are only interested in commercial aviation, then we have excluded several airports from the database (sport aviation airports without commercial passenger traffic, heliports, and airports without flight data). Once these airports have been discarded, the final network is constituted by 40 nodes and 236 links. Figures 1 and 2 show the spatial distribution of SAN airports and its regular routes, respectively.

4. Topological Analysis of SAN

4.1. Basic Metrics, Degree, Strength, and Related Topics. SAN is a high-density network; $d = 0.303$ with average degree $<k> = 11.8$ similar to other airport networks in the literature (see Table 3). Airports of Barcelona, Madrid, and Palma de Mallorca are the highest-degree nodes of SAN, i.e., those with the highest number of direct connections within the Spanish domestic air transport system. These cities called hubs are the very most touristic and business destinations of Spain and play a central role in passenger distribution over the SAN.

The characterization of the cumulative probability distribution of node degree of a concrete real network is a crucial structural issue reflecting how far this concrete real network is from a random network. While ER networks have Poisson degree distribution approximately bell shaped, many real networks are potential.

Figure 3 represents the cumulative degree distribution of SAN in a log-log scale. Potential behaviour is observed, but the slope of log-log plot clearly presents a decreasing knee, so airports with a low degree (less than a critical value of k_c direct connections) are much more likely than those with

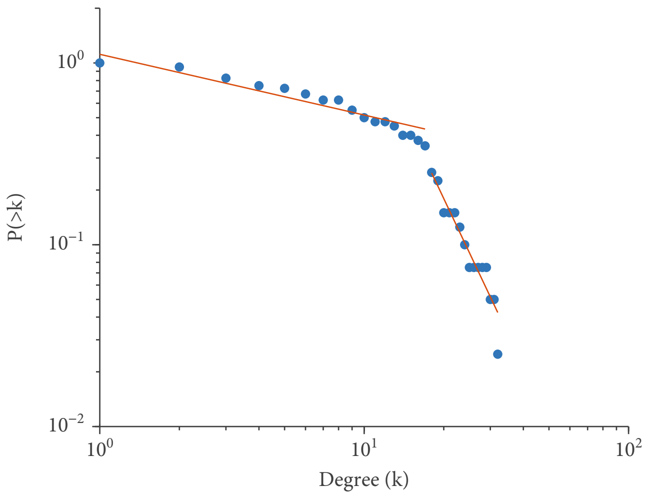

Figure 3: Accumulative degree distribution of SAN nodes fitted by a double Pareto law (log-log scale).

Table 4: Parameters of double Pareto degree law distributions of some airport networks [19, 21] and SAN.

Airport network	n	Critical degree knee K_c	α	β
SAN	40	17	0.33	3.07
IAN	42	9	0.2	1.7
CN	144	28	0.51	2.79
EU	467	60	0.8	4.23
US	657	7	0.72	3.99

a higher degree. Cumulative degree distribution of SAN can be fitted to a double Pareto law distribution.

$$P(>k) = \begin{cases} ak^{-\alpha}, & k \le k_c, \\ bk^{-\beta}, & k > k_c. \end{cases} \quad (2)$$

SAN shares this property with other airport networks like Italian (IAN), United States (US), European (EU), and Chinese (CN) airport networks [19, 21] (see Table 4). SAN has the highest β-slope related to α; thus, its degree distribution rapidly decays for degrees greater than 17. This is mainly due to the fact that SAN has a small number of highly connected airports having direct routes with many secondary airports with similar importance in SAN structure.

The power double Pareto law suggests that SAN also belongs to the class of scale-free networks.

Degree is the first simple metric to measure the connectivity of a node. Nevertheless, we are also interested in SAN weighted by traffic flow. Node strength quantifies node relevance not only by its direct neighbours but also by the traffic it handles. Turning to SAN data, an increasing correlation between degree and average strength is observed (see Figure 4). Strength and degree relationship can also be fitted by a potential law, that is to say, $s(k) \propto k^{\alpha}$ ($\alpha = 2.70$). The larger an airport is, the more connections it has and the more traffic it handles.

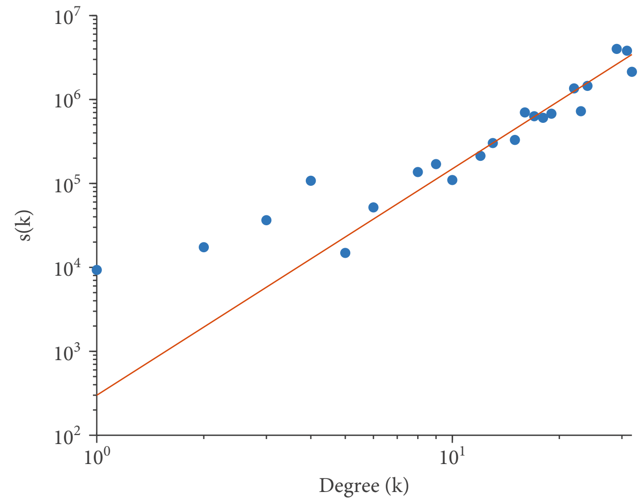

Figure 4: Node strength fitted by a potential law (log-log scale).

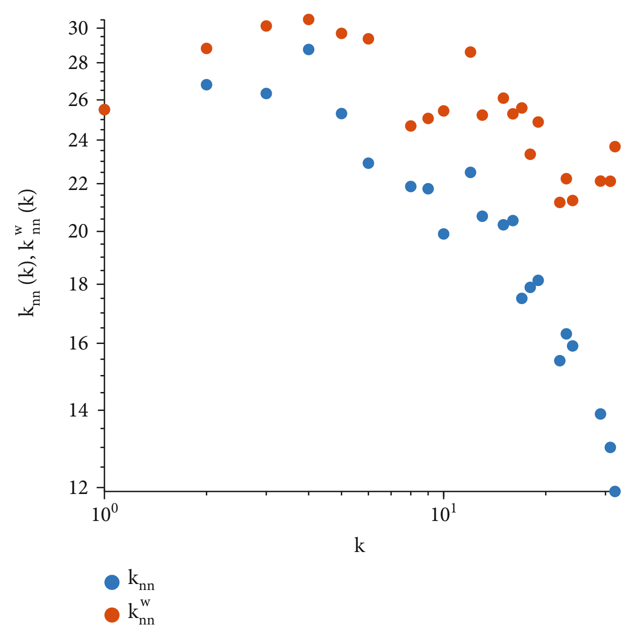

Figure 5: Average degree of the nearest neighbors of k-degree nodes. Unweighted and traffic-weighted SAN.

On the other hand, degree correlations are shown in Figure 5. Both unweighted and weighted average metrics $k_{nn}(k), k^w_{nn}(k)$ are decreasing functions of k. It means that high-degree nodes are connected to lower ones and we say that SAN has a disassortative behaviour. We observe that average degree is lower than average strength; the higher k is, the more pronounced the difference is. It means that SAN has disassortative topology, but traffic is concentrated between high-degree nodes. According to this behaviour, degree correlation of SAN takes a negative value ($r = -0.45$).

4.2. Clustering. Dealing with connectivity capacity, clustering coefficient of SAN is $C = 0.73$, much greater than the corresponding value of a RE random network with the same

Table 5: Shortest path lengths.

Shortest path length	% of routes	% of routes (weighted)	Transfers
	30.3%	30.3%	0
	64.0%	60.5%	1
	5.7%	9.1%	2
	—	0.1%	3

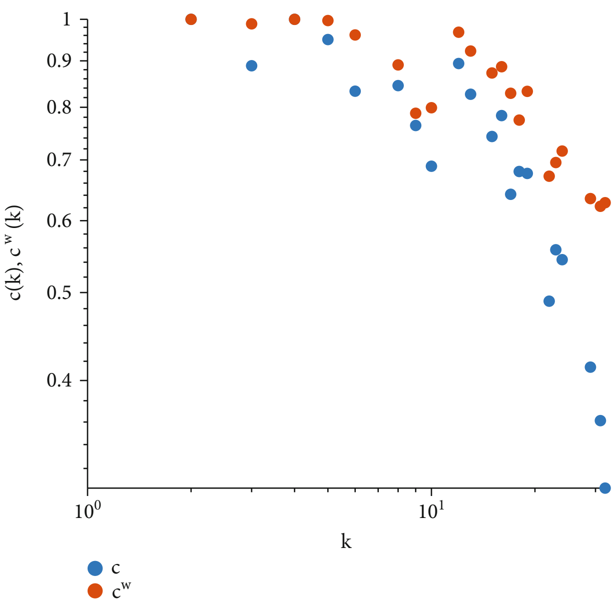

Figure 6: Clustering. Unweighted and traffic-weighted SAN.

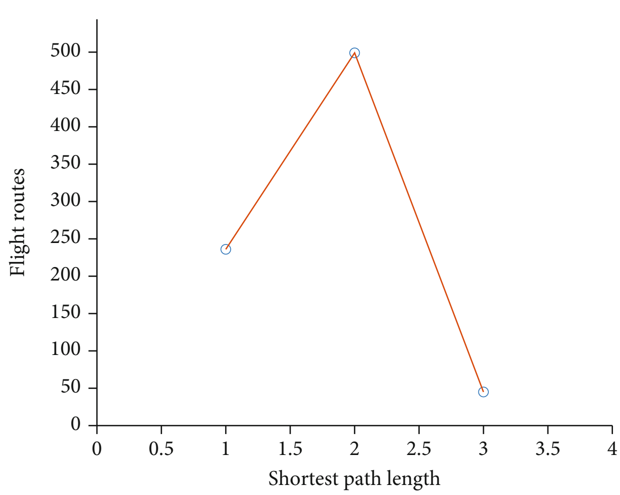

Figure 7: Shortest path length.

number of nodes and edges ($C = 0.30$). This property also implies that SAN is a small-world network.

Figure 6 shows clustering coefficients of k-degree nodes $C(k)$ and their corresponding weighted measures. Both coefficients are decreasing functions of k. Thus, large airports called hubs provide air connectivity to far-off and secondary airports of SAN, which do not tend to be connected themselves.

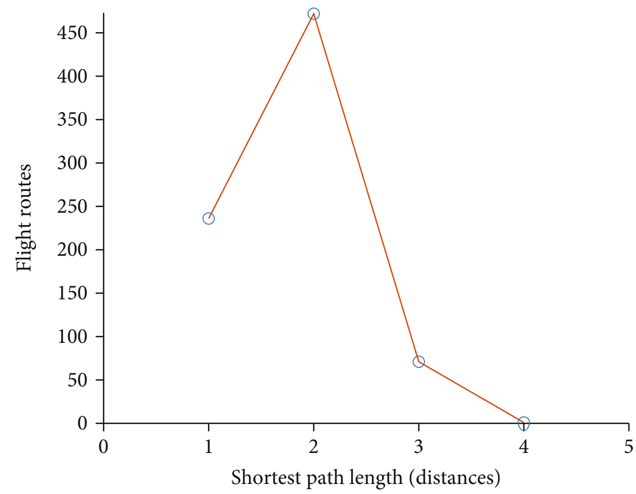

Figure 8: Shortest path length weighted by orthodromic distances.

As we comment before, SAN is a well-connected network with high clustering coefficient C and average clustering coefficients for fixed degree k are consequently high for almost all k. On the other hand, if we take into account the passengers traffic flow of SAN, weighted clustering coefficient $C^w = 0.83$ is greater than the corresponding unweighted coefficient. Moreover, Figure 6 shows that the unweighted values $C(k)$ of average clustering coefficients are clearly lower than their corresponding weighted values $C^w(k)$ for all k, and the more neighbours a node has, the more distance between the coefficients. This is called "the rich club phenomenon"; that is to say, although the trend of large airports is to be connected to few cliques, those cliques have "rich" nodes with the highest traffic, that is, the triplets that are formed between large airports with both many direct connections and passenger traffic.

4.3. Shortest Paths. The average shortest path length is $L = 1.76$, and diameter is $D = 3$. This means that most flights are directed or have one stop, and the maximum number of stops is 2. This gives an idea of how easy and fast is flying within the Spanish domestic airport network.

Table 5 compares SAN's shortest path lengths when the network is weighted by geographic distances versus the unweighted case. Note that there are no relevant differences between both cases. Average measures $L = 1.76$ and $L^w = 1.79$ are similar though the weighted diameter is $D^w = 4$ and $D = 3$. That difference follows from a single route of weighted length 4 (see Figures 7 and 8). In fact, SAN is a dense network with short distances between airports.

4.4. Efficiency, Damage, and Node Importance by Centrality. Finally, SAN is a highly efficient network $E = 0.64$, doubling the efficiency $E = 0.36$ of the WAN world network.

Table 6 shows damage values considering the top five airports whose disconnection supposes a greater damage on the network. Airports are also ordered by strength,

Table 6: Comparison of several metrics quantifying the importance of airports of SAN. Top five damage nodes.

Airport	Damage rank (D_i)	Strength rank (s_i)	Degree rank(k_i)	C_B rank	C_E rank	C_C rank
Madrid-Barajas	1 (10.39)	1 (4,004,490)	3 (29)	2	2	3
Tenerife Norte	2 (9.36)	5 (1,355,192)	$6^{(â)}$ (22)	4	$8^{(ââ)}$	$6^{(ââ)}$
Palma de Mallorca	3 (9.21)	3 (2,136,272)	1 (32)	1	3	1
Barcelona-El Prat	4 (7.29)	2 (3,809,771)	2 (31)	3	1	2
Gran Canaria	5 (6.43)	4 (1,452,415)	4 (24)	5	4	4
Málaga	6 (6.19)	9	5	6		
Alicante-Elche	7 (5.83)	19	7	7		
Bilbao	8 (5.79)	7	8	10		
Sevilla	9 (5.79)	8	9	13		
Valencia	10 (5.69)	12	10	12		

degree, betweenness centrality, eigenvector centrality, and closeness centrality. Rankings are consistent, the same five airports appear in the top five except Tenerife-Norte with rank number 6 by degree ($k_i = 22$), and the closeness centrality rank equals 6 with eigenvector centrality ranking 8. In both rankings, Malaga-Costa del Sol ($k_i = 23$) comes in position 5; hence, it is a central node due its direct connections to the principal Mediterranean airports and Madrid.

These top five clearly point to the Spanish cities with the highest economic impact of Spain, Madrid and Barcelona, and the principal Mediterranean and tourist island cities of Spain, Malaga, Tenerife, Palma de Mallorca, and Gran Canaria, as the most central airports of the Spanish domestic airport system.

5. Conclusions

We find that SAN is a small-size, highly connected network with high density, similar to other developed economies like Italy or Australia. The average shortest path shows that most of connections between airports are direct or need only one flight transfer. At most, 3 flights are needed to reach any airport from any other. The SAN is found to be the SW network. This fact has been observed in several countries in the literature. A disassortative pattern has been observed. It means that national hubs provided connectivity to a large number of low-degree destinations. High-degree airports are negatively correlated with their clustering coefficient, so they are surrounded by lower-degree fair-off airports which do not tend to be connected themselves. Rich club phenomenon is also observed. High-degree airports are the most central in terms of betweennes. SAN has high efficiency, which hardly is affected by falls or inactivity of one isolated airport. The airports of Madrid, Barcelona, Palma de Mallorca, Tenerife, and Gran Canaria are at the forefront in terms of the volume of passengers and play a crucial role in connectivity with other peninsular territories of Spain or international connections on the touristic sector. They are also the most sensible nodes if its activity could be temporally stopped in case of catastrophes, terrorist attacks, or other potential threats.

Data Availability

We use the OAG database (OAG Analyzer) which is available upon request at webpage https://www.oag.com/.

Disclosure

A preliminary study of the topological properties of the SAN was presented by P. Sáinz Puente as her final bachelor thesis in Aerospace Engineering.

Conflicts of Interest

The authors declare no potential conflict of interests.

Authors' Contributions

Both authors conceived and planned the work, wrote the manuscript, processed the experimental data, performed the analysis, and contributed to the interpretation of the results.

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