A Network Analysis of the Greek Parliament and some Socio-Economic Issues

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Abstract
In this paper we provide some insights in the structure of the Greek Parliament from the perspective of social network analysis. We use historical and publicly available data to create a social network (i.e. a graph) that comprises of all members of the Greek Parliament for a period of 80 years, together with their interactions. We present a visualization of these data and calculate some well-established metrics, coming from social network analysis in this social network. Our results indicate that the Greek Parliament Network (GPN) is a small-world network, rather dissasortative and very difficult to disconnect. We finally argue that this network may be prone to produce corruption in its general sense.

Keywords: social network analysis, small worlds, politics, Greek parliament, assortativity coefficient, scale-free networks

Jel Classification Codes: Z10, C1, A14

Introduction and motivation

In the recent years, Greece has been suffering from a very severe financial crisis. There has been a lot of public discussion on the reasons that lead the Greek state to such a hard position and, of course, many different scholars, politicians and journalists try to explain the situation. Many reasons, mostly macroeconomic ones have been proposed and widely accepted as playing a role in the "Greek drama", however, it seems that the political position of the person that proposes such reasons is bounded by its political thesis.

However, to our knowledge, almost everybody in Greece, regardless of his/hers political view, agrees that one of the main reasons that lead Greek Economy (and of course Greek society) in such a harsh position is corruption. Certainly, the notion of corruption is quite broad. One can realize many different aspects of corruptive behaviour since by definition "corruption is perversion or destruction of integrity in the discharge of public duties by bribery or favour" (Oxford English Dictionary, 2010). In (Granovetter, 2007) it is reported that recent literature is dominated by economic treatments that focus on identifying structures of incentives that make corruption more likely and on assessing the impact of corruption on economic efficiency. Such arguments are usually framed in terms of agency theory, where a corrupt individual is an agent betraying a principal who has vested fiduciary obligations in him. In such treatments, the relationship between agent and principal is defined by how incentives are arranged, and the actors are otherwise indistinguishable or "representative" individuals. Granovetter also argues that although such models may be reasonable, other things equal, in practice they underdetermine outcomes because they abstract away from the social aspects of how incentives come to be arranged as they are and how they come to be endowed with the value and the meaning that they ultimately have for actors. These important questions lie largely outside an economic frame of reference and require analysis of social, cultural, and historical elements.

Having in mind the above "wise" direction, we have decided to focus on one of the largest, most historical and probably one of the most influential public organizations in Greece: the Greek Parliament. We will use techniques and tools from Social Network Analysis to represent a simplistic model of the Greek parliament, calculate a set of well defined metrics on it, compare it with other real life networks and discuss these results in the context of weather its structure favours corruption in any way.

Network theory or social network analysis theory is a mature theory which can help exploring the nature of interconnected unities (Wassermann and Faust, 1994). This theory first emerged by Moreno (as noted in Scott, 2000), a field anthropologist, and then studied successively within Graph Theory, a branch of pure mathematics started from Euler. Graph Theory has been playing a central role in Computer Science ever since Harary's modern introduction in 1969 (Harary, 1969). Social Network Analysis has been one of the fields with exploding research in the past twenty to thirty years, yielding extensive literature, both in textbooks and journals. SNA ideas and results have been extensively used in many applications and cases, ranging from structural anthropology to marketing and banking and from viral infection to sociology.

In the following sections we organise our presentation as follows: In Section 2, we present some terminology and basic indexes used in topological network analysis. In Section 3 we will present the networks we have assembled. These networks are used in Section 4 were we calculate our metrics, compare them with other real-life or artificially created networks and discuss our numerical results. A final discussion and future perspectives is outlined in the last section.

Network theoretical terms

In pure mathematics, a graph G consists of the pair (V, A), where $V = \{v_1, v_2, \dots, v_N\}$ is the finite set of vertices (or nodes, or actors) of cardinality $|N|$ and $A = \{l_1, l_2, \dots, l_L\}$ is the finite set of links (or edges) of cardinality $|L|$, where $l_k = (v_i, v_j)$, $v_i, v_j \in V$ and $l_k \in A$. When the pair (v_i, v_j) is ordered, then the graph is called directed and we talk about arcs instead of links, otherwise the graph is undirected. Every directed graph can be simplified as an undirected one, however in this procedure there is a loss of probably important information. Links of the type *(v_i, v_i)*, when allowed, are called loops. Finally, there are cases where more than one links connect the same pair of nodes, in other words there can be multiple lines in a graph. When a graph has by default no multiple lines and no loops, it is called a simple graph.

When one or more weights are assigned to each link, this graph is called a network. However, in recent literature as in Hanneman and Riddle (2005), the two terms (graph and network) are not distinguishable in this manner. A graph is also a network and a network with weights on its links is met as a valued network.
One of the most important features of graph (or network) theory is the fact that every network can be drawn on the plane or in three dimensions. In this way, the overall structure of the network is shown in a pictorial way, which in turn can help us discover (otherwise difficult to find) properties. There exist a number of techniques (see Pajek, 2007) available for drawing each with certain advantages and disadvantages. We will use the most prominent ones like MDS (multidimentional scaling) and spring embedding.

A *path* is a sequence of vertices, where each vertex is written only once and there exists a link connecting two subsequent vertices. The *length* (of a path is the number of "hops" needed to complete the path.

A graph is called *disconnected* when there exist at least two nodes not reachable to each other. Some nodes play a very important role here, since their removal disconnects the graph. When the removal of one node leaves the graph disconnected, then it is called an *articulation points* connecting different *bi-components*.

There are a large number of different data structures which can be used to store a network in a computer's memory. One of the most straightforward ones (Gross and Yellen (2004)) is the adjacency matrix *A*, which is a NXN matrix where:

$$\mathrm{A}_{i,j} = \begin{cases} 1, \mathit{if}\ \ \mathrm{v_i} \text{ is connected to } \mathrm{v_j} \\ \quad 0, \text{otherwise} \end{cases}$$

Traditionally we investigate nodes in a network regarding their overall position, with respect to all other nodes. We thus try to find which (if any) nodes are more *important* than others. A common technique is to measure the *centrality* index of nodes and compare all nodes according to this index. We will use three different measurements of centrality, namely *degree, closeness* and *betweenness* centrality (see Sec.4.1 for precise definitions).

However, in recent literature, there is a shift in the perspective from which we examine a network, leaving individual nodes and regarding more general, topological issues that hold over the whole network. Newman (2002a), has assembled a set of metrics regarding the topology of a simple, undirected network. We will use this approach since it has been reported as the most important and concise. More specifically we will deal with *link density, degree, distance, diameter, eccentricity, clustering coefficient, assortativity coefficient* and *algebraic connectivity*.

Link Density, *S*, is the ratio of the actual number of links, L, divided by the maximum possible number of links that could exist in a network. Obviously, in a network with *N* nodes, the maximum possible number of links will be exactly

$$\frac{N(N-1)}{2}$$

which is the case of a complete graph where each node is connected to all other N-1 nodes of the network. Thus, link density is calculated as:

$$S = \frac{2L}{N(N-1)}$$

and can take values in [0..1].

The *Degree*, d_i, of node v_i is the number of links emanating from v_i. In directed networks we have to deal with in-degree and out-degree (link going to a node and links leaving a node respectively), however we will deal only with undirected networks. Since every link contributes to two nodes, the average degree of the network can be easily calculated as:

$$E(d_i) = \frac{2L}{N}$$

The *Distance* between two nodes v_i and v_j is the length of the shortest path that connects v_i to v_j. The average distance of a network is the average of all distances in this network.

The *Diameter, D,* of a network is the longest distance over all pairs of nodes.

The *Eccentricity* of a node is the largest distance from this node to any other node in the network. All node eccentricities can be averaged, yielding the average eccentricity of the network.

The *Clustering Coefficient*, CC_i, of node v_i, is the ratio of the actual number of links of v_i's neighbours, divided by the maximum possible number of links in this neighbourhood. If a node has large clustering coefficient, then its neighbours tend to form highly interconnected clusters. If v_i has exactly *K* neighbours which interconnect with *M* links between them, then CC_i is calculated as:

$$CC_i = \frac{2M}{K(K-1)}$$

The average on all *CC's* for all the nodes of a network is the average clustering coefficient of the network.

The Assortativity Coefficient, *R*, of a network, can take values in *[-1, 1]* and is calculated as follows:

$$R = \frac{L^{-1}\sum_i j_i k_i - \left(L^{-1}\sum_i \frac{1}{2}\left(j_i + k_i\right)\right)^2}{L^{-1}\sum_i \frac{1}{2}\left(j_i^{\,2} + k_i^{\,2}\right) - \left(L^{-1}\sum_i \frac{1}{2}\left(j_i + k_i\right)\right)^2}$$

where j_i and k_i are the degrees of the nodes at the ends of the i-th link, and $i=1..L$. The calculations needed are somehow complicated; however R denotes the degree-similarities between neighbouring nodes. When R is less than zero, a node is connected with other nodes of arbitrary degrees. However, when R is greater than zero and closing to one, nodes tend to connect with other nodes with similar degrees (assortative networks).

The Algebraic *Connectivity* of a graph, studied by Chung (1997), is the second smallest eigenvalue of its Laplacian Matrix. The Laplacian Matrix of a graph G with N nodes is the NXN matrix $Q=\Delta-A$, where A is the adjacency matrix of G and $\Delta=diag(d_i)$. The larger the algebraic connectivity, the more difficult it is to find a way to cut a graph to many different components.

Formation of the Greek Parliament Network (GPN)

When we try to assemble a network, two critical questions arise (Wasserman and Faust, 1994):

a. Where are the actual data?

b. Who are the *'actors'* in the network? The answer to this question will yield the set of nodes.

c. How do we define the *'relation'* between those actors? Obviously, the answer to this question will yield the set of links.

These three questions are not so easy to answer. Regarding question 1, collecting data can be a very tedious or even extremely difficult task, especially when these data are historical and not in digital form. The Library of Greek Parliament has edited a large volume which presents all members of Parliament (MPs), from 1929 up to 1974, however these come in a very large pdf file which was produced by scanning images of handwritten pages. We had to use these files for the period that begins in 1929 and ends in 1974, since after that year and up to 2011, all MPs were stored digitally on the Greek Parliament site. As for question 2, in a network that represents human entities, an actor will most probably represent a human. Hence, our nodes are all the MPs that serviced during the above period. There exist exactly 2,787 such nodes.

After the formation of the set of nodes, we have to decide on the definition of the relation between them. However, this relation can take quite different meanings, especially when we try to investigate real-life situations. For example we may choose to relate actors if the like each other, if they hate or dislike each other, in they fight to each other or if they cooperate. In each one of these cases, different networks will be produced, since the links will differ, despite the fact that the set of nodes will be the same. In the network we investigate, a line is drawn between two nodes when the corresponding actors 'interact' in some way. We use the terms 'interaction' in the sense that if two MPs happen to serve during the same time period, then those MPs will certainly interact, regardless of the context. It must be emphasized that this is the simplest, most general form of interconnection and therefore 'most dangerous' in the sense that it does not incorporate a homogenous interpretation. A more suitable definition of relations is a prospect of future work. All in all, there exist exactly 930,314 such links, connecting the 2,787 nodes[1].

[1] All relevant data are available via e-mailing to dkydros@teiser.gr

In Fig. 1 we present GPN, created following the above discussion. We have used the proposed methods from the literature, as noted in Pajek (2007) and Borgatti, Everett and Freeman (2002) (Ucinet), namely an initial application of Fruchterman-Reighgold spring-embedding algorithm, followed by a number of applications of the Kamada-Kawai algorithm, which brings closer nodes with high interconnectivity.

Structural and Numerical Analysis

From Fig. 1, some important features of the network emerge in a straightforward manner. It is therefore obvious that the graph is *connected*, that is, all nodes are reachable from all the others. This is a not so easily expected result, especially in Greece were during the time period investigated, there have been two dictatorships, the Second World War and a civil war. In two time periods, namely from 1936 to 1946 and from 1967 to 1974, the Greek Parliament was suspended. Obviously, even after those historical periods, a reasonable number of MPs resumed their positions and were re-elected, thus serving as bridges between those time periods. It can also be easily seen in Fig. 1 that MPs fall in two large chunks of nodes which represent the time period before and after the dictatorship (1967-1974).

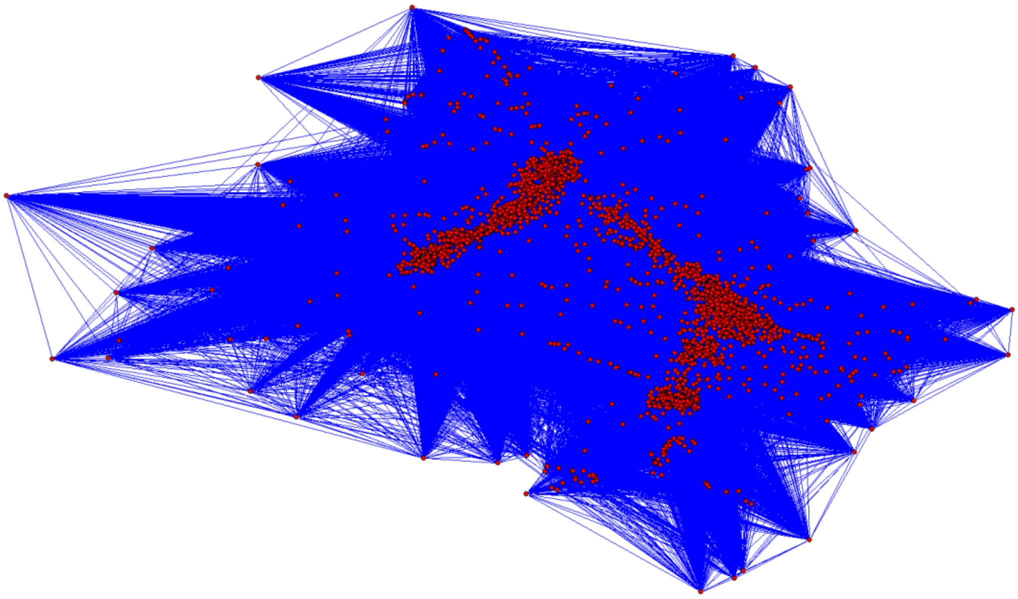

Figure 1: A drawing of the full simple GPN

Centrality issues

Important nodes in the network can emerge in terms of *centrality* measurements. In network analysis it is typical to use and compare three different measurements of centrality, namely *degree*, *closeness* and *betweenness* centrality, which will be briefly explained in terms of their natural meaning.

a. In *Degree* centrality we measure the degree of each node. It can be argued that if a node is involved in many interactions, then this is an important node, playing an important role. However, this type of centrality focuses on the local view of immediate neighbours and sometimes leads to misleading perceptions.

b. The *Closeness* centrality of vertex *v* is a summary measure of the distances from *v* to all other vertices; the number of other vertices divided by the sum of all distances between v and all others. Intuitively, shorter distances to other vertices should be reflected in a vertex's larger closeness score. In this sense, one can think of closeness as reflecting compactness. For reasons of easy interpretation we inverse this score, so actors with a higher score are more important than others.

c. The *Betweenness* centrality of a vertex v is the proportion of all geodesics between the pairs of vertices which include v. The more a vertex is needed for, say, passing of information between all the pairs, the higher is its score. In this sense, one can think of betweenness as reflecting facilitation of circulation. Nodes with high values regarding this measurement act as brokers in communication.

In Table 1, we present the fifteen most prominent nodes (in Greek) with respect to their scores in all three centrality measurements.

Table 1: The fifteen most prominent actors regarding centrality

Rank	Node	Degree	Node	Closeness	Node	Betweenness
1	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΕΜΜΑΝΟΥΗΛ Β.	2,320	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΕΜΜΑΝΟΥΗΛ Β.	*0.8567*	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΕΜΜΑΝΟΥΗΛ Β.	*0.0498*
2	ΜΗΤΣΟΤΑΚΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Κ.	2,166	ΜΗΤΣΟΤΑΚΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Κ.	*0.8180*	ΘΕΟΤΟΚΗΣ ΣΠΥΡΙΔΩΝ Ι.	*0.0386*
3	ΘΕΟΤΟΚΗΣ ΣΠΥΡΙΔΩΝ Ι.	1,986	ΘΕΟΤΟΚΗΣ ΣΠΥΡΙΔΩΝ Ι.	*0.7769*	ΑΝΑΓΝΩΣΤΟΠΟΥΛΟΣ ΓΕΩΡΓΙΟΣ Θ.	0.0340
4	ΜΠΟΥΤΟΣ ΙΩΑΝΝΗΣ Π.	1,866	ΜΠΟΥΤΟΣ ΙΩΑΝΝΗΣ Π.	*0.7518*	ΜΗΤΣΟΤΑΚΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Κ.	*0.0326*
5	ΑΒΕΡΩΦ - ΤΟΣΙΤΣΑΣ ΕΥΑΓΓΕΛΟΣ Α.	1,818	ΑΒΕΡΩΦ - ΤΟΣΙΤΣΑΣ ΕΥΑΓΓΕΛΟΣ Α.	*0.7421*	ΒΑΡΒΙΤΣΙΩΤΗΣ ΜΙΛΤΙΑΔΗΣ Ι.	*0.0261*
6	ΚΑΡΑΜΑΝΛΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Γ.	1,811	ΚΑΡΑΜΑΝΛΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Γ.	*0.7408*	ΚΑΡΑΜΑΝΛΗΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Γ.	*0.0166*
7	ΡΑΛΛΗΣ ΓΕΩΡΓΙΟΣ Ι.	1,796	ΡΑΛΛΗΣ ΓΕΩΡΓΙΟΣ Ι.	*0.7378*	ΚΟΝΙΤΣΑΣ ΘΕΜΙΣΤΟΚΛΗΣ Ι.	*0.0165*
8	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΙΩΑΝΝΗΣ Κ.	1,787	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΙΩΑΝΝΗΣ Κ.	*0.7361*	ΣΠΗΛΙΟΠΟΥΛΟΣ ΚΩΝΣΤΑΝΤΙΝΟΣ Γ.	*0.0163*
9	ΚΟΝΙΤΣΑΣ ΘΕΜΙΣΤΟΚΛΗΣ Ι.	1,785	ΚΟΝΙΤΣΑΣ ΘΕΜΙΣΤΟΚΛΗΣ Ι.	*0.7357*	ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΙΩΑΝΝΗΣ Κ.	*0.0145*
10	ΛΑΥΡΕΝΤΙΔΗΣ ΙΣΑΑΚ Ν.	1,778	ΛΑΥΡΕΝΤΙΔΗΣ ΙΣΑΑΚ Ν.	*0.7343*	ΚΑΡΑΜΑΝΛΗΣ ΑΧΙΛΛΕΥΣ Γ.	*0.0117*
11	ΣΤΕΦΑΝΙΔΗΣ ΜΙΧΑΗΛ Σ.	1,762	ΣΤΕΦΑΝΙΔΗΣ ΜΙΧΑΗΛ Σ.	*0.7312*	ΜΠΟΥΤΟΣ ΙΩΑΝΝΗΣ Π.	*0.0111*
12	ΤΑΛΙΑΔΟΥΡΟΣ ΑΘΑΝΑΣΙΟΣ Σ.	1,742	ΤΑΛΙΑΔΟΥΡΟΣ ΑΘΑΝΑΣΙΟΣ Σ.	*0.7274*	ΒΑΡΒΙΤΣΙΩΤΗΣ ΙΩΑΝΝΗΣ Μ.	*0.0082*
13	ΜΑΥΡΟΣ ΓΕΩΡΓΙΟΣ Ι.	1,738	ΜΑΥΡΟΣ ΓΕΩΡΓΙΟΣ Ι.	*0.7267*	ΑΒΕΡΩΦ - ΤΟΣΙΤΣΑΣ ΕΥΑΓΓΕΛΟΣ Α.	*0.0079*
14	ΖΙΓΔΗΣ ΙΩΑΝΝΗΣ Γ.	1,717	ΖΙΓΔΗΣ ΙΩΑΝΝΗΣ Γ.	*0.7227*	ΡΑΛΛΗΣ ΓΕΩΡΓΙΟΣ Ι.	*0.0074*
15	ΚΑΡΑΜΑΝΛΗΣ ΑΧΙΛΛΕΥΣ Γ.	1,706	ΚΑΡΑΜΑΝΛΗΣ ΑΧΙΛΛΕΥΣ Γ.	*0.7206*	ΛΑΥΡΕΝΤΙΔΗΣ ΙΣΑΑΚ Ν.	*0.0065*

A number of interesting observations can emerge from Table 1. Regarding degree centrality, we can see that there exist a number of authorities – hubs which connect to an extreme number of other nodes. Recalling that N=2,787 it is a big surprise to see that the top first node is connected to the 85% of all other nodes. Furthermore, all fifteen nodes connect to more than 60% of all other nodes. To anyone familiar to Modern Greek political situation, all these nodes represent MPs that have been serving during the '50s, '60s and even in the first period of '70s, right after the reinstallation of democracy. This could mean that the refreshment rate of MPs is very poor.

Another surprise comes from the fact that rankings are exactly the same regarding both degree and closeness centrality. This fact assures us that the overall structure is rather monolithic, a very tightly closed "family" were it very easy for a large number of nodes to contact or influence other actors.

Regarding betweenness centrality, the situation is somehow changed, since new nodes come forward and there exists a small rearrangement in the rankings. Again, to all those familiar to politics, these MPs served almost continuously during the '60s and '70s and even the '80s or '90s !.

Overall, it should be noted that the actual numbers in all three rankings are quite high compared to other social networks, especially when we include the time period during which GPN is formed. We will discuss this comparison furthermore in the next subsection, when we calculate more metrics on this and other networks.

Numerical Results and comparison to other networks

In this section we present our numerical results. Apart from Pajek, in order to obtain the most recent topological metrics, i.e. assortativity coefficient and algebraic connectivity, we used *NetworkX* from Hagberg, Schult and Swart (2008), a Python-based package for the creation and manipulation of networks and *igraph* for R by Csardi and Nepusz (2006), a similar package, and we developed some code, written in Python and R, to calculate these metrics.

In Table 2 we present the actual numbers for all the metrics defined in Section 2, compared to other well known and investigated networks from the literature (Jamakovic, 2007).

Table 2: Some network metrics and comparisons

Metric	**Value**				
	GPN	**DST**	**BSP**	**ACT**	**INT**
Num. of Nodes (N)	2787	691	13411	10143	20906
Num. of Links (L)	930314	10450	315566	147907	42994
Density	*0.239*	*0.044*	*0.0035*	*0.0029*	*0.0002*
Average Degree	*667.609*	*30.25*	*47.10*	*29.16*	*4.11*
Assortativity Coefficient	*-0.022*	*-0.063*	*0.12*	*0.026*	*-0.20*
Average Distance	*1.851*	*4.49*	*3.29*	*3.71*	*3.89*
Diameter	*3*	*11*	*--*	*13*	*11*
Average Eccentricity	*2.601*	*8.59*	*--*	*9.57*	*8.03*
Av. Clustering Coefficient	*0.822*	*0.75*	*0.79*	*0.76*	*0.21*
Algebraic Connectivity	*39.332*	*0.16*	*--*	*0.0004*	*0.015*

In Table 2., DST represents a network comprised of the Dutch Soccer National Team players (over a period of 80 years), BSP is similar bur with Brazilian players, ACT is a network of Actors playing in the same movies and INT is a snapshot of interconnected routers at the autonomous system level. We decided to include these (and not others) networks because they all incorporate a large period of time during witch they were formed.

The average *Link Density, S*, equals *0.239*. The meaning of this metric is that in GPN there exists almost 24% actual links over the maximum possible number of links. The network is definitely extremely dense; actually, its density cannot be compared to all other networks and furthermore we have not been able to identify any real-life network that is so dense (we can always create dense networks in laboratory conditions or in very small real graphs). The *Average Degree,* $E(d_i)$, is *667.609*, meaning that in average, every MP has interacted with (close to) 667 other MPs. The actual degrees vary from 121 to 2320 *(ΚΕΦΑΛΟΓΙΑΝΝΗΣ ΕΜΜΑΝΟΥΗΛ Β.)*. There are no pendant nodes (degree=1).

A more interesting result is the average *Distance*, the average shortest path over all actors. An average value of 1.851, means that we can generally find a path of this length between any two pairs of actors. Reversely, a *Diameter* of value 3 means that the longest geodesic (the longest shortest path) is again very small. The path that actually achieves this value starts from node *'ΦΙΚΙΩΡΗΣ ΙΩΑΝΝΗΣ'* (1974 to 1997) and ends on *'ΖΗΣΙΜΟΠΟΥΛΟΣ ΑΝΤΩΝΙΟΣ'* (1929 to 1931).

It is a surprise to see that these steps are not close to the value of 6, which in turn is exactly the number proposed by Watts and Strogatz (1998) and others, known widely as the *"six degrees of separation"* principal, which holds for a vast number of different real-life networks. Our results indicate with no doubt that GPN does not follow this principal.

The extremely small average shortest path, together with the very high values of *Clustering Coefficient (0.822)* yields the very interesting property of a small - world. Indeed, as noted in Watts (1999), the relationship found between these two metrics also proves that such a network is generally a small-world. One other property of this type of networks is the existence of a small number of hubs (nodes with very high degree), while all other nodes have relatively small degrees. All actors (and some more not listed) from Table 1 are actually hubs.

The negative value for the *Assortativity Coefficient, (R=-0.022)*, reveals that within GPN actors do not tend to interact with other actors possessing a similar degree. If *R* was equal to 1, then all actors would connect to others with exactly the same degree. On the other hand, if *R* was -1, then all actors would connect to others with different degrees in an extreme manner (i.e. hubs with pendants). In our case, however we cannot draw a stable conclusion from such a value. This result is in contradiction to the generally accepted principle of *homophily* in real-life networks, i.e. the general belief that nodes tend to connect to similar nodes, regarding one property. Of course, the particular relation examined on one network does influence this metric: friendship ties do indeed behave differently than other ties. However, recent results found in Newman (2002b), indicate that homophily is generally met in human interaction networks, where human psychological factors play a very important role or networks freely formed in nature, whereas the opposite holds for networks formed in economy and business. For example, Newman (2002b) has found that large banks tend to lent money in small banks – not in other large banks. GPN definitely should belong to the first category since the process of its formation over time should obey the general sociological rules.

Our final result, *Algebraic Connectivity* (39.3), is a measurement of the general robustness of the networks. Small values would indicate that the networks are easily cut in disconnected components. A value of zero (0) means that the network is already disconnected. In Chung (1997) it is reported that this metric is bounded below by 1/(N*D) and in fact by 4/(N*D). Algebraic Connectivity is upper-bounded by the traditional connectivity of a network, that is, by the size of its smallest cut-set, meaning that it takes the removal of about 40 nodes to disconnect this network.

Final discussion, Conclusions and further Research

In this paper we investigated the Greek Parliament Network (GPN) through the perspective of Social Network Analysis. We prepared a data set of interactions between actors and formed a network with the assistance of some Python code and software like Pajek. In turn, we investigated some structural features of this network and calculated some important topological metrics.

In many cases, especially when we tried to compare GPN to other real-life networks, we came to a surprise. This network, despite the fact that was created during a very large period of time, does not follow the expected norms; instead it looks more and more like an artificially created network. The main issue here is the extreme density and the very small diameter. Every MP, all over time, can reach every other MP in two steps. Of course, because of natural reasons, this does not happen in reality but can be traced through historic documents or through hubs with extremely large centrality properties. A definite result is that this network does not change as expected through time. Some MPs service period span over three or even four decades.

GPN thus is a rather monolithic organization. When almost everyone can reach almost everyone else, then an extremely notion of consensus is easily met. Metrics like the ones presented in the previous section, are met only in families or in organizations like the army where everyone is expected to interact to each other or to work with each other for a special purpose. One can easily deduce that GPN does not generally act as a network but as a single node in many cases. Actually, it is common knowledge in Greece that whenever an MP is prosecuted for criminal reasons, a large number of others vote in favour of a form of asylum, to protect their colleague. A great deal many such criminal cases, including accusations for corruption, have stopped or halted in this way.

It is interesting to see that despite the usual "charged" political climate in Greece, when it comes to investigating corruption, it seems that the whole Parliament, through subtle movements and law manipulation, moves as a whole trying to stop, halt or postpone its decisions. We argue that density and small geodesics is the main reason for such a behaviour. This organization acts and reacts more like a family that protects its members than a political organization.

Some steps can be taken in order to reverse this situation, over time. In order to increase paths and reduce density, a simple way to achieve this would be to prohibit any MP from being re-elected more than once. The use of a list of candidates instead of the "crossing" system in elections (where voters use the sign of the cross to note their preference on one of many candidates), would help. Any measure that would overcome this excess power in a modern democratic way, like frequent public referendums, would be very helpful. Similar measures that could lead to such a directions have many times been discussed in public fora, but, as already mentioned, it seems that whenever such a discussion arises nothing is really done (the system protects itself and its members - a really corruptive behaviour).

Our approach can be researched and discussed in more detail in the future. One thread would be to compare GPN with other Parliament networks (i.e. the European Parliament or the Italian Parliament), using the same metrics we used here. It would be interesting to explore, for example, if density is so large in a country of the European South or smaller. Again, it will be interesting to try to create a mathematical model that produces such networks, since the well-known models of Barabasi or Watts are not so helpful in generating such a graph. Finally the data could be used to form different networks, perhaps in smaller periods of time or by partitioning the nodes according to the political parties they belong. A very interesting but extremely hard (due to lack of automated data mining techniques) would be to identify relations of kin in this network in order to investigate nepotism.

From the sociological or political aspect of view, it would be very interesting to clarify the reasons why GPN produces such a condensed or monolithic behaviour. Of course such an approach should be discussed with scholars that specialize in such fields.

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