Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 3 / August 2020

GEOGRAPHICAL AND SOCIOECONOMIC DETERMINANTS IN THE TOPOLOGY OF SPATIAL NETWORKS: EVIDENCE FROM THE INTERREGIONAL ROAD NETWORK IN GREECE

Dimitrios TSIOTAS
Department of Planning and Regional Development, University of Thessaly, Pedion Areos, Volos, 383 34, Greece
tsiotas@uth.gr

Labros SDROLIAS
General Department, University of Thessaly, Pedion Areos, Volos, 383 34, Greece
lsdrolias@teilar.gr

Georgios ASPRIDIS
General Department, University of Thessaly, Pedion Areos, Volos, 383 34, Greece
aspridis@teilar.gr

Ioannis PAPADIMOPOULOS
General Department, University of Thessaly, Pedion Areos, Volos, 383 34, Greece
j_papdim@otenet.gr

Abstract
This paper studies the interrelation between the topology of spatial networks and their geographic and socioeconomic framework, based on empirical data extracted from the interregional road network in Greece (GRN), aiming to interpret how this road network serves and promotes the regional development. The study conceptualizes network topology as the composition of a set of major topological measures extracted from complex network analysis (CNA) and it configures the network's spatio-socioeconomic framework by a set of geographical, infrastructure, demographic, and productivity attributes, all of which are computed in regional scale. Within this context, the aggregate network topology of GRN is approximated by a system of multivariate linear regression models, with response variables each of the available measures of network topology and with predictors all the available spatio-socioeconomic variables. The analysis shows that the topology of GRN is submitted to intense spatial constraints and that is being configured to facilitate the requirement of industrial development, implying that this infrastructure network has a primary developmental functionality. Overall, this paper promotes interdisciplinary research between regional economics and physics by using the network paradigm and it provides insights about using network topology as a socioeconomic index of real-world applications.
Keywords: Econophysics, regional economics, network science, regional development.

1. INTRODUCTION

Road networks are the most widespread and accessible land-transportation networks because of the dominance of the car as a mode of private transport (Kurant Thiran, 2006; Polyzos, 2011; Barthelemy, 2011; Polyzos et al., 2014). Taking into consideration that transportation is an aspect of human communication which is subjected to unavoidable spatial constraints (Rodrigue et al., 2013, Tsiotas and Polyzos, 2015), it can be said that the structure of such networks, on the one hand, reflects over time the historical and socio-economic needs of human communication and, on the other hand, is related to the diachronic ability of the society to overcome the spatial constraints to communicate (Blumenfeld-Lieberthal, 2008; Rodrigue et al., 2013; Tsiotas and Polyzos, 2018). This double approach illustrates the complex relation between network structure and the socioeconomic framework of networks (Tsiotas and Polyzos, 2018) and it highlights the requirement for a better understanding of the socio-economic aspects of human communication through the study of transportation networks. For example, the structure, the geometry, and, generally, the shape of road networks obviously differ today than how they were in the past. Differences in structure may suggest an effect of technological evolution of transportation modes (Rodrigue et al., 2013; Polyzos et al., 2014), whereas differences in geometry (i.e. in the network shape) may occur due to changes in the socioeconomic importance of the interconnected spatial units (e.g. cities) in the network (Rodrigue et al., 2013; Tsiotas and Polyzos, 2018).

Moreover, the study of the particular historical, socioeconomic, and geographic (spatial) aspects of a transport network helps to achieve a deeper knowledge of its structure and functionality and it also facilitates its modeling process. From one aspect, provided that the construction and, generally, the development of transport infrastructure is a time-consuming process, it can be assumed that the shape and the topology of transportation networks have a significant impact on the growth and evolution of the transport sector, both at the national and the interregional level (Blumenfeld-Lieberthal, 2008; Rodrigue et al., 2013; Tsiotas and Polyzos, 2015a,b). In other words, unlike the flexibility describing immaterial (e.g. social) networks (Sgroi, 2008), the structure of transportation networks is not that flexible in timely adapting the changes caused in their socio-economic framework (Polyzos et al., 2014; Tsiotas and Polyzos, 2015b) and it depends on specific features. One of such features is the existence of spatial constraints (Barthelemy, 2011; Tsiotas and Polyzos, 2018) due to the space of embedding (Tsiotas, 2019). In particular, in road and rail transportation networks, movements mainly occur linearly, having one degree of freedom (d.f.) (Barthelemy, 2011), whereas, in maritime and aviation networks, transportation enjoys more degrees of freedom because it is conducted either on the sea-surface (2d.f.s) or in the 3d aviation-space (3d.f.s) and thus non-land-transportation is submitted to smoother

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spatial constraints than the land-transportation (Rodrigue et al., 2013). However, crossovers and multilevel network junctions may occasionally lend planarity or even non-planar configuration to land-transportation networks (Barthelemy, 2011; Rodrigue et al., 2013) and thus they can lend more degrees of freedom to the linearity of land-transportation movements. Nevertheless, the intensity of spatial constraints of land-transportation networks is still higher than the maritime or air transport networks because another feature is that road and rail transportation networks are more infrastructure-driven than the non-land networks (Polyzos, 2011; Rodrigue et al., 2013; Erdem et al., 2019). In particular, in land-transportation networks, movements occur through infrastructure channels (e.g. roads, highways, rails, etc.), whereas, in maritime and aviation networks, transportation is not restricted to a constructed space and thus the structure of land-transportation networks is more inflexible to rearrangements or restructure (e.g. rerouting). (Rodrigue et al., 2013; Polyzos and Tsiotas, 2020). In economic terms, the infrastructure-dependency of land and particularly of road networks induces high sunk costs for the development these networks, namely the expenses which were already paid for the construction of road infrastructures and which cannot be recovered are considerably high (Link et al., 2012). High sunk costs of road networks require long-term and professional planning for a sustainable road transportation policy (Alpopi et al., 2011; Colesca and Alpopi, 2011; Polyzos, 2011), which make the study of road networks' topology more important.

Greece is a, small, coastal country with geopolitical importance, which is located in the southeast Europe, between two continents (Europe and Asia) and among three seas (Black Sea, Aegean, and the Mediterranean). The area of the country is almost 132,000km2 and it includes more than 14,000km of coastline and more than 1,350 islands, islets, and rocky islands, among which over 230 are inhabited (Tsiotas and Polyzos, 2015a; Tsiotas, 2017). About the 13% of the national population is located in continental regions of Greece, covering almost the 34% of the total land area, about the 75% of the national population is located in coastal regions, covering almost the 48% of the total land area, and the remaining (~) 12% is located in insular areas, covering almost the 18% of the total land area (Polyzos, 2011; Tsiotas and Polyzos, 2015a; Tsiotas, 2017). In terms of regional productivity, the country is specialized in the tertiary sector, possessing a share of about 63-70% of the regional GDP, whereas the respective shares are about 11-15% for the primary and 16-24% for the secondary sector (Polyzos, 2011). Considerable components of the tertiary specialization in Greece are tourism, possessing a share of about 8-13% of the regional GDP (Tsiotas, 2017), and transport and communication, possessing a share of about 5-7% of the regional GDP (Polyzos, 2011). According to the General Framework of Spatial Planning and Sustainable Development of Greece (GSPF, 2008), transportation is a key component for the national and regional economic development and the development of transportation suggests a major strategic goal for the promotion of tourism, trade, and communication at all geographical scales in which the country is involved. On the one hand, the country's geopolitical position is determinative for the development of tourism, trade, and related activities (Polyzos, 2011), whereas, on the other hand, the diverse (mountainous and marine) country's geomorphology places some restrictions on the development of land transport, favoring the emergence of alternative and competitive transportation modes, such as of the maritime transport (Tsiotas and Polyzos, 2015a).

Within this context of geopolitical and economic complexity, this article studies some major topological aspects of the interregional Road Network in Greece (GRN) in comparison with some fundamental attributes of its spatio-socioeconomic framework, aiming to detect what kind of spatial and socioeconomic information is critical for the configuration of the network topology and thus to provide insights about how network topology is related regional development. To do so, the study conceptualizes network topology as the composition of a set of major topological measures (from complex network analysis) and it builds a system of multivariate regression models having the network topological measures as response variables and a set of spatio-socioeconomic variables as predictors. This approach aims at detecting which geographical and socioeconomic variables are significant predictors for each model and thus at developing quantitative links between the network topology and regional development. Overall, the examination of the interplay between the network topology of land transportation in Greece and of the spatio-socioeconomic framework of this network suggests an interesting case study capable to provide insights about how this prime mode of transportation can contribute to economic development, within a framework of intense competition due to maritime transport. The further purpose of this paper is to promote the interdisciplinary research in the field of Econophysics, by proposing a macroscopic approach for the modeling of the topology of complex networks in geographical and socioeconomic terms.

The remainder of the article is organized as follows: Section 2 presents a literature review, section 3 describes the methodological framework of the study, and particularly the graph modeling, the data and methods, the network measures, and the empirical analysis, section 4 presents the results of the analysis and discusses them through the prism of network science and regional science, and, finally, in section 5 conclusions are given.

2. LITERATURE REVIEW

Existing literature in the study of road transportation is very broad and is scattered along various disciplines, such as transportation engineering, spatial economics, spatial planning, physics, geography, and economics (Barthelemy, 2011; Polyzos, 2011; De Montis and Reggiani, 2012; Rodrigue et al., 2013; Tsiotas and Polyzos, 2018). Within the vast volume of the relevant literature, someone can discriminate three major perspectives (categories) driving the research in this field, the first is accessibility analysis (De Montis and Reggiani, 2012), the second is complex network analysis (Barthelemy, 2011), and the third suggests a mixture of the previous two.

The first category conceptualizes road transportation from the aspect of accessibility, which is a multidimensional concept composed by the core concepts of location and distance and it generally concerns the advantages benefited to those accessing a certain location by means of a particular transportation mode (Polyzos, 2011; De Montis and Reggiani, 2012; Paez et al., 2012; Rodrigue et al., 2013). A compact review on the essentials of accessibility can be found in the guest editorial of De Montis and Reggiani (2012), which prologues a special issue on accessibility and socio-economic activities, focusing on methodological and empirical aspects. The paper highlights the methodological and empirical aspects of accessibility, which is related with the concepts of cost and utility, network structure, and complexity. As the authors state, in econometric-methodological terms, accessibility has been modeled both in macro-economic and in micro-economic level. These approaches led to the development of spatial interaction models (Polyzos, 2011; Rodrigue et al., 2013), of stochastic-utility maximization models, and of a variety of accessibility indicators, measures, proxies, and variables, some of which measure travel-time, distance, and land-values (De Montis and Reggiani, 2012). Some indicative accessibility models are econometric and spatial models, such as GIS-based network-analysis and spatial autocorrelation models. According to their methodological characteristics, the authors discriminate two groups of accessibility models (De Montis and Reggiani, 2012), those which are coordinated to spatial-economic growth and those which are coordinated to activity patterns. From another point of view, Paez et al. (2012) apply an origin-based grouping of accessibility-measures, discriminating those referring to accessibility from the origin (e.g. cumulative opportunity, gravity, mean-travel cost, facility, and distance measures) from those referring to accessibility to the destination (population serviced or market shares). Another interesting perspective is that the authors discriminate accessibility-measures to normative, which are defined in terms of expectations (e.g. how far people should travel or it is reasonable to travel), and to positive, which are defined in terms of observations (e.g. how far people actually travel) (Paez et al., 2012). In general, literature of this category is focusing on the interrelation between geography and the socioeconomic activities emerging in space. For a deeper review the reader is referred to the previous works.

The second category conceptualizes road transportation from the aspect of the network paradigm (Newman, 2010; Brandes et al., 2012; Tsiotas and Polyzos, 2018), according to which road-transport systems are modeled into graphs (networks), which are non-parametric models expressing communication systems into pair sets G(V,E) that are composed by a set of nodes V and links E. In the work of Rodrigue et al. (2013), we can meet the term topological accessibility, as an attempt to describe the graph-modeling of transportation systems in terms of “nodes and paths”. This term emerged by the cognition that “accessibility is a measurable attribute significant only to specific elements of a transportation system, such as terminals (airports, ports or subway stations)” (Rodrigue et al., 2013, p.322). Networks embedded in space compose the family of spatial networks (Barthelemy, 2011; Rodrigue et al., 2013; Tsiotas and Polyzos, 2018), where transportation networks belong to. A thorough review about spatial networks can be found in the paper of Barthelemy (2011), which describes representative cases of spatial and road transportation networks from the physicists’ perspective (Tsiotas and Polyzos, 2018). According to this approach (Barthelemy, 2011), the major and simplest representation of a road network is a graph where links express roads and nodes express road-intersections or end points, whereas, in other network models, nodes may express spatial units whose links express node-interconnections and usually flows. Analysis in this category is based on topological analysis and statistical mechanics of complex networks (Barthelemy, 2011; Tsiotas and Polyzos, 2018), such as computation of network-topology measures, pattern recognition based on degree-distribution, community detection, etc. For instance, relevant empirical studies (Jiang and Claramunt, 2004; Cardillo et al., 2006; Crucitti et al., 2006; Lammer et al., 2006; Jiang, 2007) focusing on topological aspects of road networks have shown that, in macroscopic level, quantitative similarities can be found between road networks of very different cities, such as planarity, mesh-alike configuration, and bell-shaped degree distribution patterns (expressing the effect of space) instead of power-laws (expressing high-level hierarchy) (Barthelemy, 2011). In general, literature of this category is focusing on the topology of road transportation networks, namely to the relational configuration of the network elements (nodes, links) in the topological space, which is the relational (metric-less) space prior the network is embedded in a metric space (see Tsiotas and Polyzos, 2018).

The third category is a composition of the previous two and it focuses on the interplay between the socioeconomic framework, the geographical space, and the network topology of road transportation networks (Tsiotas and Polyzos, 2018). Papers belonging to this category (De Montis et al., 2007, 2011; Geurs et al., 2015; Tsiotas and Polyzos, 2018) are usually more recent and interdisciplinary than of the previous two and they build on the conceptualization that diversity in network topology of (road) transportation networks is driven by forces of the geographical and socioeconomic framework of the communication system that a network represents. Therefore, this category seems to have emerged as an effect of integrating the fruitful research that network science has already provided to applications in

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geography and transportation engineering. For instance, De Montis et al. (2007) modeled interurban commuting flows between 375 municipalities in Sardinia, Italy, into a (complex) spatial network, focusing on both the topological and the weighted properties of the resulting network. The authors characterized quantitatively the traffic backbone among large cities, they observed very high heterogeneity of commuting flows around large cities, and they discussed the interplay between network (topological and dynamical) properties with socio-demographic variables, such as population and monthly income. In the work of De Montis et al. (2011a), the authors attempt to integrate complex network analysis to methodologies adopted for constructing accessibility indicators, on data extracted from the previous interurban commuting network, in Sardinia. In particular, two commuter accessibility indicators were considered, one based on a travel-cost models and another based on a spatial-interaction model with impedance calibrated in exponential and power form. The study provided insights about hierarchy of Sardinian municipalities, with respect to their actual commuter flows, and it showed that these complex-network-based (i.e. computed on the network topology) accessibility indicators are more reliable than others, as better picturing the actual productive system of municipalities in Sardinia. In another work, De Montis et al. (2011b) studied the network dynamics of the commuting system of Sardinia and Sicily, which are the two main insular regions of Italy. Based on a degrees and strengths distribution consideration, the authors observed random-like characteristics of the topological properties of these networks but a scale-free behavior when considering the weighted network configuration (strengths), highlighting the effect of the socioeconomic framework in the network topology. The authors observed a constant rule driving the socio-demographic development of both systems, according to which “the higher the traffic handled in a town, the higher the resident population in the same town according to a power-law rule with exponent close to 2 in each year” (De Montis et al., 2011b, p.64). In epistemological terms, Geurs et al. (2015) noted that is necessary future research to focus on the relationship between accessibility and network connectivity at different scale levels (urban, regional, national, etc.) and Tsiotas and Polyzos (2018) developed a framework of integrating the study of spatial networks from the geographers’, physicists’, sociologists’, and computer scientists’ perspective.

Within this context, this paper builds on the epistemological demand of integrating interdisciplinary aspects for the analysis of road transportation networks and it thus tries to link the network topology with the spatio-socioeconomic framework of the GRN by constructing a system of multivariate linear regression models.

3. METHODOLOGICAL FRAMEWORK

The methodological framework of the study is shown in Figure 1, according to which the analysis of the GRN is implemented into three parts; the graph modeling, the multivariate regression modeling, and the empirical analysis.

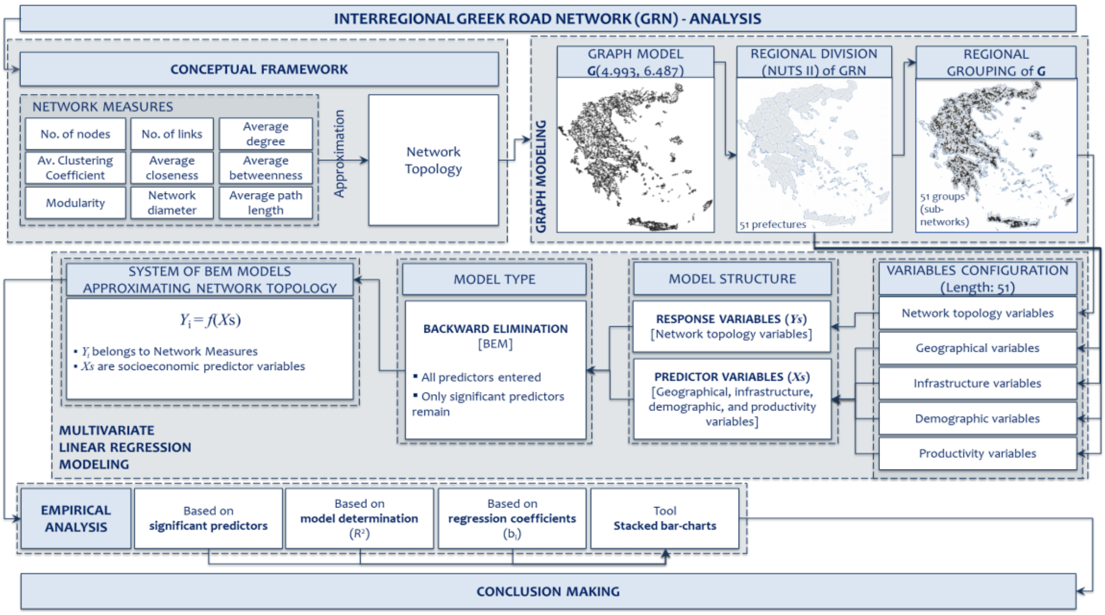

FIGURE 1 - FLOW CHART DISPLAYING THE CONCEPTUAL AND METHODOLOGICAL FRAMEWORK OF THE STUDY.

At the first part, the GRN is modeled into a graph, at the second part a system of multivariate regression models is constructed to approximate the GRN's topology, and at the third part an empirical analysis takes place. Each part of the methodological framework is described in brief as follows:

Graph modeling

At the first part, the GRN is modeled as a non-directed graph G(V, E), with n=4,993 nodes and m=6,487 edges (links). Non-directed graph-modeling was chosen because the interregional road connections included in the graph-model of GRN represent two-way road-paths in the physical network. The GRN is modeled in the L-space representation, which is also called "space of stops" (Kurant and Thiran, 2006) and it is a graph embedding used to represent the topology of transportation systems. In this representation, stops in transportation-routes define graph-nodes and geographical routes intermediating two successive nodes define links, which are drawn as linear segments regardless the geometry of their geographical route (Kurant and Thiran, 2006; Barthelemy, 2011). For the GRN, nodes (V) express (road) route intersections and edges (E) express two-way routes intermediating to these nodes (Fig.2). Nodes are placed in the geographic coordinates (complying with the WGS '84 coordinate system) of their corresponding road intersections and edges are drawn as straight lines. The link-

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weights of GRN equals to geographical distances of the network and not to line-distances of the graph model. The available data used for the GRN-model refer to the routing of the primary, secondary, and tertiary national road network, along with the primary and secondary provincial road network of Greece, as they are defined and described in the Presidential Decree ΠΔ.401/93 and they were configured into a map by the Department of Road Construction Studies, Greek Ministry of Infrastructure, Transport, and Networks. The shape-file (*.shp) of the GRN was extracted (and it is freely available) from the Greek Land Registry and Mapping Organization (OKXE, 2005).

The GRN is a disconnected network because of the diverse coastal and insular geomorphology of Greece including more than 1,350 island-formations and over 230 inhabited islands. In islands, connectivity with the mainland is achieved by maritime or air transport (just a pair of exemptions exist) (Tsiotas and Polyzos, 2015a; Tsiotas, 2017) and thus road networks serve interior needs of transportation, between places within the same island. Therefore, not all nodes in GRN are accessible to each other through network paths and thus the network is further divided into components, consisting of the major mainland component and the components of the island road clusters.

This state of disconnectedness is a problem in network science, known as insufficient connectivity (Koschutzki et al., 2005), which obstructs calculations because most of the network measures are well-defined within connected graphs (Tsiotas and Polyzos, 2015b). For instance, two nodes with the same degree may have different importance when the first belongs to a small and the second to a giant component. For overcoming this problem, several methods were proposed for repairing the insufficient connectivity (Koschutzki et al., 2005), such as the local restriction method (LRM), where local measures are converted to global (aggregate) as they are, without any modification (restricted), the proportional conversion method (PCM), where local measures are weighted proportionally to the size of the components they belong to, the arbitrary fixed values method (FVM), where an arbitrary (based on the researcher's intuition) value is set to define the infinite distance between disconnected nodes, and the cumulative nomination method (CNM), where the weighting of the local measures is based on a stepwise process of evaluating the neighbors connectivity for successive distances (d=1,2,3,… steps). Each method has its benefits and drawbacks and it is appropriate depending on the modeling framework and the purpose of the research. In this study, using the simplest LRM is a satisfactory choice for repairing the insufficient connectivity of GRN because this network is infrastructural and thus the underlying restriction of planarity is enough so that two nodes, with the same degree which belong to unequal components, to have the same importance for the aggregate network. Therefore, GRN has no special physical interpretation for applying more advance repairing insufficient connectivity methods.

Besides, in the regional scale, the regional groups can be loosely considered to be of equivalent size and thus the precision that other methods will give to the analysis is expected to be inconsiderable.

Multivariate regression modeling

The second part of the methodological framework includes the multivariate regression modeling. At first, topological and spatio-socioeconomic (vector) variables are configured on data extracted from fundamental network measures the GRN graph-model's topology and from the GRN's geographical and socioeconomic framework. The network measures considered for the formation of the topological variables of GRN are shown in Table 1.

TABLE 1 - NETWORK MEASURES CONSIDERED FOR THE FORMATION OF THE GRN'S TOPOLOGICAL VARIABLES

Measure	Description	Math Formula	Reference
Network size (n)	Number of nodes in the network $G(V,E)$, where V expresses the node-set and E the edge-set.	$n=\|V\|=\text{card}\|V\|$	Newman (2010)
Links (m)	Number of edges in the network $G(V,E)$.	$m=\|E\|=\text{card}\|E\|$	Newman (2010)
Node Degree (k)	Number of the edges adjacent to a given node, expressing the node's communication potential.	$k_i = k(i) = \sum_{j \in V(G)} \delta_{ij}$, where $\delta_{ij} = \begin{cases} 1, & \text{if } e_{ij} \in E(G) \\ 0, & \text{otherwise} \end{cases}$	Newman (2010)
Network diameter $d(G)$	The longest path in the network.		Newman (2010)
Local Clustering Coefficient ($C(i)$)	Probability of meeting linked neighbors around a node, which is equivalent to the number of the node's connected neighbors $E(i)$ (i.e. the number of triangles), divided by the number of the total triplets shaped by this node, which equals to $k_i(k_i-1)$.	$C(i) = \frac{E(i)}{k_i \cdot (k_i - 1)}$	Barthelemy (2011)
Average Path Length $\langle l \rangle$	Average length $d(i,j)$ of the total of network shortest paths.	$\langle l \rangle = \frac{\sum_{v \in V} d(v_i, v_j)}{n \cdot (n-1)}$	Newman (2010)
Modularity (Q)	Objective function expressing the potential of a network to be subdivided into communities. In its mathematical formula, g_i is the community of node $i \in V(G)$, $[A_{ij} - P_{ij}]$ is the difference of the actual minus the expected number of edges falling between a particular pair of vertices $i,j \in V(G)$, and $\delta(g_i,g_j)$ is an indicator function returning 1 when $g_i=g_j$.	$Q = \frac{\sum_{i,j} [A_{ij} - P_{ij}] \cdot \delta(g_i, g_j)}{2m}$	Blondel et al. (2008); Fortunato (2010)

Measure	Description	Math Formula	Reference
Closeness Centrality (*CC*(*i*))	Total binary distance *d*(*i,j*) computed on the shortest paths originating from a given node *i* with destinations all the other nodes *j* in the network. This measure expresses the node's reachability in terms of steps of separation.	$CC(i) = \frac{1}{n-1} \cdot \sum_{j=1, i \neq j}^{n} d_{ij} = \overline{d}_i$	Koschutzki et al. (2005).
Betweenness Centrality (*CB*(*i*))	The proportion of the (σ) shortest paths in the network that pass through a given node *i*.	$CB(i) = \sigma(i)/\sigma$	Koschutzki et al. (2005)

Based on these measures, a set of network-topological, geographical (approximated by the G group), and socioeconomic, such as infrastructure (approximated by the I group), demographic (approximated by the D group), and productivity (approximated by the P group) variables are constructed to participate in a multivariate linear regression analysis, as shown in Table 2. This approach conceptualizes network topology as the composition of a set of network variables and builds a system of multivariate linear regression models to approximate the network topology of GRN.

TABLE 2 - VARIABLES(*) PARTICIPATING IN THE ANALYSIS OF GRN

Code	Name	Description	Source
A. Network-topology variables (*N*)			
N_1	*NODES*	The number of GRN nodes included in each prefecture.	Own elaboration based on the GRN model (OKXE, 2005)
N_2	*EDGES*	The number of GRN edges included in each prefecture.	
N_3	*ADEG*	The average degree of the GRN's sub-network included in each prefecture.	
N_4	*AC*	The average clustering coefficient (unweighted) computed on each prefectural sub-network of the GRN.	
N_5	*ACC*	The average score of closeness centrality (unweighted) computed on each prefectural sub-network of the GRN.	
N_6	*ACB*	The average score of betweenness centrality (unweighted) computed on each prefectural sub-network of the GRN.	
N_7	*MOD*	The score of the modularity function (Q) computed on each prefectural sub-network of the GRN.	
N_8	*D*(*G*)	The diameter (unweighted) of the GRN's sub-network included in each prefecture.	
N_9	*AL*	The average path length (unweighted) computed on each prefectural sub-network of the GRN.	
	B. Spatio-socioeconomic variables		
	B_1. Geographical variables (*G*)		
G_1	*COASTAL*	(Dummy variable) Binary index showing whether a region is coastal or not.	Own elaboration based on Google Maps (2017)
G_2	*ISLAND*	(Dummy variable) Binary index showing whether a region is island or not.	
G_3	*INLAND*	(Dummy variable) Binary index showing whether a region is inland or not.	

Code	Name	Description	Source
G_4	*AREA*	The area of each prefecture (×1000m²).	Own elaboration based on the GRN model (OKXE, 2005)
G_5	*TL*	The tilling (crop) land area within each prefecture (×1000m²).	(ELSTAT, 2015)
G_6	*FORESTS*	The forest area within each prefecture (×1000m²).	
G_7	*IW*	The area of inland waters within each prefecture (×1000m²).	
G_8	*LA*	The land areas within each prefecture (×1000m²).	
G_9	*SMA*	The semi-mountain areas within each prefecture (×1000m²).	
G_{10}	*MA*	The mountain areas within each prefecture (×1000m²).	
	B₂. Infrastructure variables (I)		
I_1	*RAIL*	(Dummy variable) Binary index showing whether a region has rail infrastructure or not.	Own elaboration based on Google Maps (2017)
I_2	*PORT*	(Dummy variable) Binary index showing whether a region has port infrastructure or not.	
I_3	*AIRPORT*	(Dummy variable) Binary index showing whether a region has airport infrastructure or not.	
I_4	*PORTS*	The number of ports included in each Greek prefecture.	(Tsiotas and Polyzos, 2015a)
I_5	*AIRPORTS*	The number of airports included in each Greek prefecture.	(Tsiotas and Polyzos, 2015b)
	B₃. Demographic variables (D)		
D_1	*POP*	Regional population based on the 2011 Greek census.	(Tsiotas and Polyzos, 2015a)
D_2	*URB*	The urbanization index of each prefecture, which corresponds to the population of its capital city.	(Polyzos et al., 2015)
	B₄. Productivity variables (P)		
P_1	*GDP*	The participation of each prefecture to the Gross Domestic Product (GDP) of Greece.	(Polyzos, 2011)
P_2	*A_{SEC}*	Primary sector specialization. The (%) participation of primary sector to the configuration of the prefecture's GDP.	(Tsiotas and Polyzos, 2015a)
P_3	*B_{SEC}*	Secondary sector specialization. The (%) participation of secondary sector to the configuration of the prefecture's GDP.	
P_4	*C_{SEC}*	Tertiary sector specialization. The (%) participation of tertiary sector to the configuration of the prefecture's GDP.	
P_5	*T_{GDP}*	Tourism specialization. The (%) participation of tourism to the configuration of the prefecture's GDP.	
P_6	*VIPE*	(Dummy variable) Binary index showing whether a region has industrial area or not.	(Polyzos, 2011)

*. Each vector variable includes (has length) 51 elements, which are scores of each Greek prefecture to the certain attribute

In particular, each (vector) variable of network topology (number of nodes, number of links, average degree, average clustering coefficient, average closeness centrality, average betweenness centrality, modularity, network diameter, and average path length) is entered as a response variable (Y) to a

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multivariate linear regression model and all the other variables available in Table 2 are included as predictors in each model. The backward elimination method (BEM) is used in the analysis, which starts with the full model including all of the available predictors (independent variables) and provides a sequence of models, where the most insignificant predictors are removed successively (one per loop), among those with significance (p-value) p ≥ 0.1. For a given set of predictor (independent) variables Xn={x1, x2, ..., xn}, the sequence of the BEM response (dependent) variables (yk)k≥0 is described as follows:

$$
\left(\mathbf{y}_k\right)_{k\in\{1,\dots,n\}\subseteq\mathbf{N}}\left|\mathbf{y}_k = \sum_{i=1}^{n-k+1} b_i\cdot\mathbf{x}_i + c_k\cdot\mathbf{1} = f_k(\mathbf{x}_i)\right.
\begin{cases}
X_n = \{\mathbf{x}_1,\mathbf{x}_2,\dots,\mathbf{x}_n\},\\
\mathbf{x}_i \in X_{n-k+1},\\
X_{n-k} = X_{n-k+1} - \{\mathbf{x}_p\}\\
\mathbf{x}_p \in X_{n-k+1} : P[b(\mathbf{x}_p)=0] = \max\{P[b_i=0]\geq 0,1\}
\end{cases}
\qquad (1)
$$

The final (optimum) BEM model includes only significant predictors, where the standardized coefficients quantify the participation of each predictor to the model (Tsiotas and Polyzos, 2015a,b). For all of these regression models, 95% confidence intervals are computed for the tests, and the missing values are excluded pair-wisely, namely in which the sample sizes of the pairs are redefined from test to test (Norusis, 2004; Walpole et al., 2012).

Within this context, the nine-model linear regression system (let it be vector f) approximating the network topology of GRN, let it be vector nGRN=(N1, N2,…, N9), is described by the following formula:

$$
\mathbf{n}_{GRN} \cong \mathbf{f}(G_1:G_{10},I_1:I_5,D_1,D_2,P_1:P_6) = \begin{cases}
N_1 = f_1(G_1:G_{10},I_1:I_5,D_1,D_2,P_1:P_6)\\
N_2 = f_2(G_1:G_{10},I_1:I_5,D_1,D_2,P_1:P_6)\\
\vdots\\
N_2 = f_9(G_1:G_{10},I_1:I_5,D_1,D_2,P_1:P_6)
\end{cases}
\qquad (2),
$$

where f=(f1, f2, …, f9) is the vector-functional form of the system, where each function fi, i=1,2,…,9, represents a linear regression (BEM) model defined in relation (1) and variables inside the parentheses are described in Table 2.

Empirical analysis

The empirical analysis of the GRN aims to quantify interrelations between the network topology and the road network's geographical and socioeconomic framework, in multivariate linear regression terms. Towards this direction, variables participating in the analysis (shown in Table 2) are defined at the regional (per prefecture) reference (NUTS III level). The regional level was chosen to define the spatial units due to data availability and particularly because socioeconomic data (such as demographic, productivity, labor, sectorial, educational, etc.) in Greece are kept by the National Statistical Service (ELSTAT, 2015) into regional (and particularly into prefectural, NUTS III) records. Therefore, for the sake of compatibility, variables of network topology are also defined at the regional scale and thus regional sub-networks were configured in the GRN graph-model (see Fig.1). Within this context, the available variables participating at the analysis are of length 51, namely they include 51 components (elements), each of which corresponds to one of the Greek prefectures.

In general, constructing multivariate regression models for not large sample size has been subjected to criticism (Green, 1991; Maxwell, 2000) for not providing satisfactory results. An endless academic dialogue about how the desired sample size leading to satisfactory results can be computed has emerged. In algebraic terms (Chen, 1998), a linear system with m variables can be solvable when $n=m$ equations are available and the determinant of the coefficients of the independent variables' matrix is not singular. Therefore, in order the math expression of the linear regression model not to degenerate into a classic linear system, sample sizes greater than m ($n>m$) are required to provide statistical solution (i.e. a solution including an error term) to the model. In terms of statistical inference, a sample size of $n \geq 30$ is also required to produce confidence intervals calculated with reference to the normal distribution (Walpole et al., 2012) and, thus, this condition is also applicable for interval-estimations of the regression coefficients. Also, in parameter estimation, such as in cases of estimating the mean μ or the proportion p of a distribution, the required sample size n can be expressed as a function of the statistical power (defined as the complementary probability of the type II error β, namely 1-β), the level of significance (α), the standard deviation (σ), and the standard error e (Walpole et al., 2012). This rationale is the basis of an approach known as "power analysis of hypothesis testing" (Green, 1991; Maxwell, 2000), which produces estimates for the required sample size when a desired statistical power and statistical significance are chosen. Due to the complexity of performing power analysis for the sample size estimation, some rules-of-thumb, which comply with the power analysis requirements but are easier to remember, have been proposed instead. A pair of such rules-of-thumb is expressed by the inequality $n \geq 50 + 8m$ (obtained for the multiple correlations of the model) and by the inequality $n \geq 104$

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+ m (obtained for the partial correlations of the model) (Green, 1991), where m is the number of predictors. Within this context, applying multivariate linear regression analysis requires over 100 cases so that the model to have a sufficient power (around 0.80) (Green, 1991; Maxwell, 2000), which is a condition that is not satisfied by the 51-elements sample size that is available in this study. However, by taking into consideration, first, that the approach in this paper builds on comparative analysis and thus restrictions are commonly applicable to all models, and, secondly, that the analysis focuses more on the signs of the regression coefficients rather than on their accurate arithmetic values per se, the authors believe that the previous restrictions do not suggest a considerable concern for the quality of the results obtained by this approach.

Within this context, the empirical analysis builds on the system of multivariate linear regression models approximating the network topology of GRN and it evaluates the regression results based on three approaches; the first regards the significant predictors' information, the second the determination ability (R2), and the third the regression coefficients (bi) of the models. The aggregate consideration of these approaches highlights the predictors that are, in common, important for the system of the multivariate linear regression models and thus it distinguishes the most significant determinants of the network topology of the GRN, as this concept is approximated by the nine-model linear regression system. The overall approach proposes a methodological framework for the, in common, modeling of various topological aspects in complex networks, based on a vector-wise consideration similar with rationale where the multilayer network modeling (Boccaletti et al., 2014) has been developed.

4. RESULTS AND DISCUSSIONS

The results of the analysis are shown in Table 3 and they are organized into two sub-tables. The first (Table 3a, "Model Determination"), shows the determination ability (expressed by the coefficient of determination, R2) of each regression model (Y=Yi, i=NODES, EDGES, …, AL). In this sub-table, cases that are shown in bold-font display high-determination (HD) models satisfying the inequality R2 > 0.75. The second sub-table (Table 3b, "Model Coefficients"), displays the significant standardized coefficients (beta) included in each model. In this sub-table, columns correspond to a single regression model (Y=Yi), whereas rows a predictor variable, among the available X=Xj (j=COASTAL, ISLAND,…, VIPE). Empty cells in this sub-table imply non-significant contribution of the corresponding predictor (Xj) variable to the model (Yi).

According to Table 3a, the models N1 (NODES), N2 (EDGES), N5 (ACC), N8 (D(G)), and N9 (AL) have high determination ability, implying that the variability of their predictor variables describe, in a satisfactory level (≥ 75%), the variability of the response variable (Norusis, 2004). For each of the other cases (N3, N4, N6, N7), the R2 is below marginal determination (R2 < 0.5) and thus no safe information can be extracted about the models' coefficients. First, the model N1 (number of nodes) is significantly described by the predictors G2, G3, G4, G6, I3, P1, P3, P5, and P6. Based on the predictors' physical meaning, the model's specialization implies that bigger in size (with bigger number of nodes) road networks are more probable to meet in regions (prefectures) with bigger areas (either inland or island), but not in those with large forest areas. These results highlight the interrelation between road networks' size and the need of land-space to develop them, which is a primary factor for the development of road transport networks (Polyzos, 2011; Rodrigue et al., 2013). Also, regions with airport infrastructures are more probable to have bigger road networks. This result complies with the empirical observations highlighting the complementary role of road and air transportation (Polyzos, 2011; Rodrigue et al., 2013).

TABLE 3 - RESULTS OF THE GRN'S EMPIRICAL ANALYSIS

a. MODEL DETERMINATION

Y=	*NODES*	*EDGES*	*ADEG*	*AC*	*ACC*
R^2	**0.918**[(a)]	**0.799**	0.397	0.367	**0.784**

a. MODEL DETERMINATION (CONTINUED)

Y=	*ACB*	*MOD*	*D(G)*	*AL*
R^2	0.414	0.431	**0.758**	**0.738**

b. MODEL COEFFICIENTS

Code	*Y=* / *X*	*NODES* [N_1] b[(b)]	Sig.[(c)]	*EDGES* [N_2] b	Sig.	*ADEG* [N_3] b	Sig.	*AC* [N_4] b	Sig.	*ACC* [N_5] b	Sig.
G_1	*COASTAL*			**0.414**	**0.003**						
G_2	*ISLAND*	**0.133**	**0.055**			0.382	0.026			**-0.505**	**0.000**
G_3	*INLAND*	**0.114**	**0.034**					-0.440	0.001		
G_4	*AREA*	**1.162**	**0.000**	**1.045**	**0.000**	1.112	0.000				
G_5	*TL*					-0.531	0.016			**-0.483**	**0.003**
G_6	*FORESTS*	**-0.306**	**0.000**	**-0.301**	**0.017**					**0.182**	**0.061**
G_7	*IW*										
G_8	*LA*									**0.381**	**0.013**
G_9	*SMA*										
G_{10}	*MA*					-0.668	0.005				
I_1	*RAIL*										
I_2	*PORT*			**-0.378**	**0.008**						
I_3	*AIRPORT*	**0.182**	**0.005**	**0.301**	**0.004**						
I_4	*PORTS*					-0.817	0.000	-0.458	0.003		
I_5	*AIRPORTS*			**-0.218**	**0.050**					**-0.284**	**0.009**
D_1	*POP*										
D_2	*URB*										
P_1	*GDP*	**-0.702**	**0.020**	**-1.496**	**0.005**					**-0.859**	**0.017**
P_2	*A_{SEC}*									**0.268**	**0.014**
P_3	*B_{SEC}*	**0.182**	**0.002**	**0.234**	**0.013**			0.356	0.010	**0.198**	**0.034**
P_4	*C_{SEC}*										
P_5	*T_{GDP}*	**1.642**	**0.000**	**2.373**	**0.000**			1.476	0.004		
P_6	*VIPE*	**-0.958**	**0.000**	**-0.847**	**0.024**	0.282	0.089	-1.278	0.011	**0.944**	**0.010**

b. MODEL COEFFICIENTS (CONTINUED)

Code	*Y=* / *X*	*ACB* [N_6] b	Sig.	*MOD* [N_7] b	Sig.	*D(G)* [N_8] b	Sig.	*AL* [N_9] b	Sig.
G_1	*COASTAL*								
G_2	*ISLAND*	-0.504	0			**0.322**	**0.005**	**0.280**	**0.016**
G_3	*INLAND*			0.230	0.072	**-0.175**	**0.056**	**-0.234**	**0.014**
G_4	*AREA*			0.325	0.009			**0.858**	**0.000**
G_5	*TL*					**-0.389**	**0.013**	**-0.393**	**0.014**
G_6	*FORESTS*								
G_7	*IW*								

Code	Y= X	ACB [N_6] b	Sig.	MOD [N_7] b	Sig.	D(G) [N_8] b	Sig.	AL [N_9] b	Sig.
G_8	LA					**0.683**	**0**	**0.341**	**0.039**
G_9	SMA					**0.535**	**0**		
G_{10}	MA					**0.483**	**0**		
I_1	RAIL								
I_2	PORT								
I_3	AIRPORT								
I_4	PORTS			-0.280	0.091	**-0.444**	**0.001**	**-0.433**	**0.001**
I_5	AIRPORTS			0.504	0.004				
D_1	POP	-5.556	0.001					**0.301**	**0.007**
D_2	URB			-0.365	0.005				
P_1	GDP	5.691	0.001						
P_2	A_{SEC}								
P_3	B_{SEC}								
P_4	C_{SEC}								
P_5	T_{GDP}								
P_6	VIPE					**0.268**	**0.018**		

a. HD models, with high coefficients of determination (≥ 0.75), are shown in bold font
b. Standardized regression coefficient (beta)
c. 2-tailed significance
(see names of predictor variables in Table 2)

In terms of productivity (as it is approximated by the P group of predictors), the N1 model describes that regions with high GDP are less likely to have big, in size, road networks, but those with high specialization to tourism may have, which highlights the symbiotic relation between tourism and transport (Tsiotas, 2017). Also, impressively enough, regions with bigger road networks are likely to specialize to secondary sector but less likely to be equipped industrial areas, implying that the industrial areas in Greece have deficient road-connectivity support.

Next, the model N2 (number of edges) is significantly described by predictors G1, G4, G6, I2, I3, I5, P1, P3, P5, and P6. These results imply that road networks equipped with more links are more likely to meet in regions with larger geographical areas and with coastal areas, implying that transportation in coastal area is ruled by more complexity. Also, regions with airport infrastructures are more probable to have bigger road networks, but not those with more, in number airports, and with port infrastructures. On the one hand, the result about the inverse signs between the I2 and I3 predictors imply the competitive role between maritime and air transportation in Greece (Polyzos, 2011). On the other hand, the inverse signs between the I3 and I5 predictors imply that although regions with airport infrastructures are more probable to have road networks with more links, this is not the case when the number of airports included in a region grows. Namely, regions with more, in number, airports are less likely to have bigger road networks, implying that, in regions, agglomeration of air-transport facilities begin performing competitive to the road infrastructure. In terms of productivity, the N2 model has the same significant predictors with the same as N1, describing a similar picture with the number of nodes.

The model N3 (average clustering coefficient) is significantly described by predictors G2, G5, G6, G8, I5, P1, P2, P3, and P6. These results imply that regions with higher clustered road networks with (and thus with more triangular paths) are less likely to be island and to have big tilling-land areas, but is more likely to have big forest areas. This result probably highlights the circular (bigger than triangular) or bus-alike (i.e. a major axis with branches in its both sides) or star-alike (one hub with radial connections) patterns observed in many islands and tiling areas, where such patterns in road routes exist (circular, bus-alike, and star-alike topologies have zero clustering). The positive contribution of G8 predictor shows that clustering is a privilege of land-areas, were space is plenty to develop triangles. Also, regions with airport infrastructures are less likely to have road networks with high clustering, implying that airport infrastructures facilitate the development of more zero-clustering road-accessibility patterns in their broader areas. In terms of productivity, regions with road networks of high clustering are less likely to have high GDP, but more likely to have specialization to primary and secondary sectors and also to include industrial areas.

Next, the model N8 (network diameter) is significantly described by predictors G2, G3, G5, G8, G9, G10, I4, and P6. Comparatively to the previous models, N8 is constructed by more time-invariant (belonging to the G group) predictors, which complies with the distance-based configuration of the measure of network diameter. This configuration imply, first, that more distant road networks (not in kilometric terms, but in the number of links included in the longest path) are more likely to meet in island regions and in regions with larger land areas, semi-mountain, and mountain areas, and less likely in inland regions and in regions with greater tilling land areas. The existence of G8-G10 predictors imply the effect of spatial constraints to the configuration of road networks (Rodrigue et al., 2013; Tsiotas and Polyzos, 2018), whereas the other G-predictors illustrate the reduction of topological distance when networks serve more organized activities (Polyzos, 2017). This observation is supported by the negative contribution of predictor I4 to the model, implying that regions with port infrastructures are less likely to have bigger road networks. Finally, regions with more distant road network are more likely to have industrial areas, complementing the picture shaped by the previous models.

Finally, the model N9 (average path length) is significantly described by predictors G2, G3, G4, G5, G8, I4, and D1. Based on a distance-based measure, the G-group of significant predictors in this model is similar with this of N8, with some differences about the absence of mountainous-based variables and the contribution of the area (G4) variable to the model. This implies that average path length is indifferent to mountainous morphology but it depends on the total area where the road network is embedded. Also the existence predictor I4 implies that regions with port infrastructures are less likely to have road networks with, on average, more distant path-lengths, supporting the previous observation about the reduction of topological distance when networks serve more organized activities. However, highly populated regions are more likely to have more distant path-lengths, loosely implying a tendency of networks to reduce their topological complexity (as it is expressed by average path length) in cases where other dimensions of complexity in the network (such as the regional population utilizing the network) increases.

The previous consideration provided some useful insights about the topological aspect of GRN and of their significant spatio-socioeconomic predictors. However, for reducing the complexity of the relevant information, the results of Table 3 are tabulated into the stacked bar-charts of Fig.2, which display the number of models where each predictor is significant and the stacked values of the model coefficients (beta), distinguishing between the HD models and the aggregate case.

According to Table 3 and to Figure 2, the most significant spatio-socioeconomic variables contributing to the topology of the GRN (as it is expressed by the 9-component topological system) refer to morphological (ISLAND, INLAND), to geographical (AREA, TL), to infrastructure (VIPE, PORTS), and to productivity (GDP, BSEC) attributes. Whether considering only high determination (HD) models, the previous picture of hierarchy slightly changes and a couple of geographical variables (FORESTS, LA) enter the group. This implies, first, that overcoming the spatial and geomorphological constraints is a major force in the GRN's configuration and, secondly, that the topology of the GRN seems to be developed to serve productivity needs and mainly those related to the secondary sector (BSEC). Surprisingly enough, the GRN's topology seems not to be significantly affected (at least directly) by demographic forces, since variables of population (POP) and urbanization (URB) appear significant only in 2 and 1, out of nine, models (and in 1 and 0 HD models), respectively. This observation is opposed to the gravitational rule describing transportation movements in the geographical space (Barthelemy, 2011; Tsiotas and Polyzos, 2018), according to which population is expected to play a key-role also to the configuration of the GRN's topology. Possibly, this indifference to population-based variables is related to the singular spatial-weighted configuration of the GRN's graph-model, provided that this network is constructed without considering population-based (e.g. commuting) flows, for the configuration of network edges.

Relevant literature on this issue (De Montis et al., 2007, 2011a,b; De Montis and Regigiani, 2012; Polyzos et al., 2014) shows that networks defined on population-based flows have a considerable gravitational configuration, which is not observed in the case of GRN. A gravity-based pattern was expected to emerge in the GRN's topology because the network variables used in the nine-model linear regression system (relation 2) were computed on binary (unweighted) distances and thus they are space-indifferent, implying that the topology of GRN approximated by the nine multivariate regression models is not restricted in a space-dependent framework.

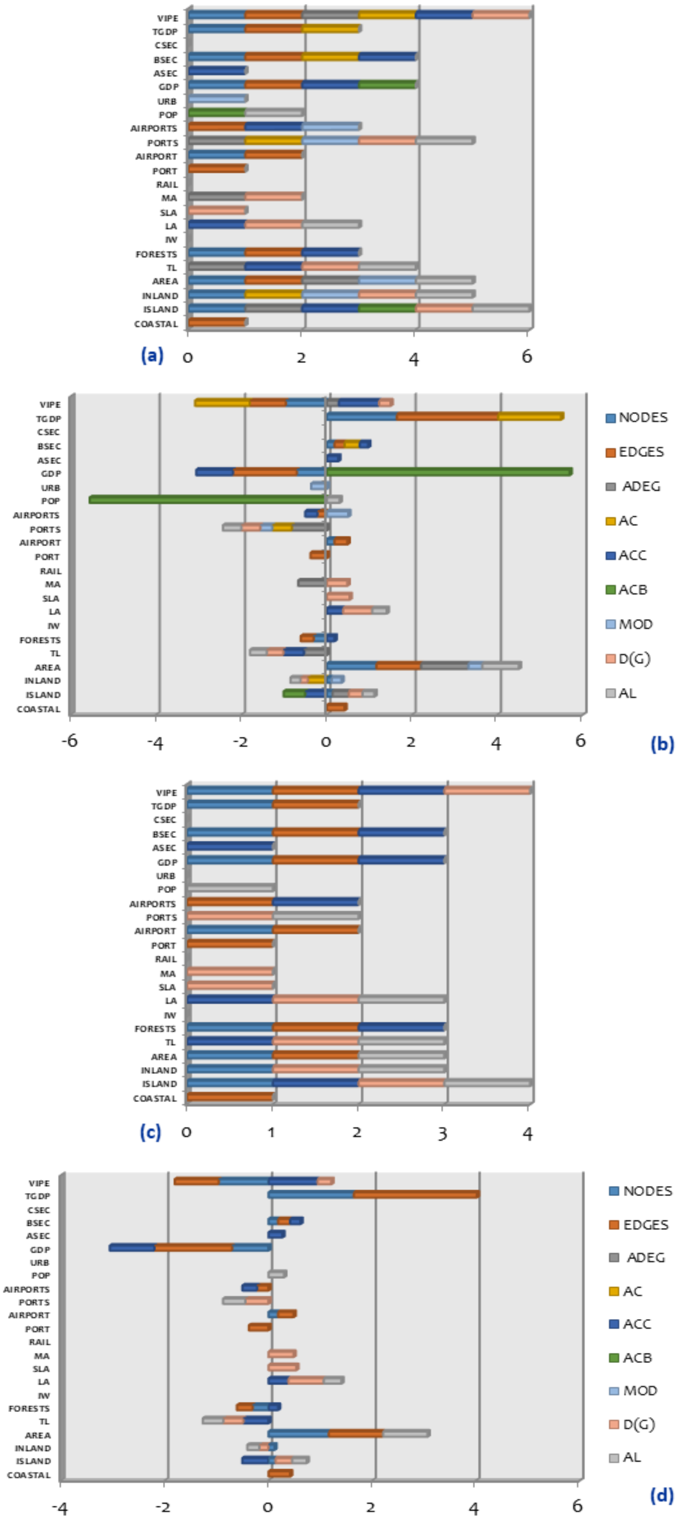

FIGURE 2 - STACKED BAR-CHARTS DISPLAYING (A) THE NUMBER OF REGRESSION MODELS (OUT OF NINE, IN TOTAL) FOR WHICH EACH PREDICTOR IS SIGNIFICANT, (B) THE STANDARDIZED VALUES OF THE SIGNIFICANT REGRESSION COEFFICIENTS (BETA) (C) THE NUMBER OF HIGH DETERMINATION (HD | R2 > 0.75) MODELS (OUT OF 5 IN TOTAL) FOR WHICH EACH PREDICTOR IS SIGNIFICANT, AND (D) THE VALUES OF THE SIGNIFICANT HD REGRESSION COEFFICIENTS (BETA). PREDICTORS IN THE DIAGRAMS ARE SHOWN AT ROWS, WHEREAS

However, an indirect presence of population can be detected in the GRN's topology, in the contribution of the productivity variables GDP and BSEC, which are population-controlled (correlated) variables (Tsiotas and Polyzos, 2015a). Therefore, the gravitational configuration of the GRN cannot be rejected, but it can be attributed to latent effects. The dependence of network topology on the edge-weights configuration in road networks suggests avenues for further research. Based on these observations, the outcome of the overall analysis shows that the topology of the GRN is restricted by the country's intense geomorphological constraints, targeting to serve the requirements of industrial development, which is a rather out-of-dated developmental pattern.

5. CONCLUSIONS

This paper studied the topology of the interregional road network in Greece (GRN) in accordance with its geographical and socioeconomic framework, aiming to detect links between these aspects and to indirectly interpret the way in which this road network serves and promotes the regional development. The GRN was modeled in the L-space representation as a non-directed graph with spatial weights. Its topological information was composed by some fundamental measures of complex network analysis (CAN) (such as the number of nodes, number of edges, average degree, average clustering coefficient, closeness centrality, betweenness centrality, modularity, diameter, and average path length), which are computed in the regional scale (NUTS III level), and its spatio-socioeconomic information was composed by a set of geographical, infrastructure, demographic, and productivity attributes. Based on these data, a system of multivariate linear regression models was constructed expressing each variable of network topology as a multivariate linear model with predictors the available spatio-socioeconomic variables.

The analysis showed that the topology of the GRN is submitted to intense spatial constraints and it facilitates the requirement of industrial development, since higher values of the network topology variables are met in regions that have industrial areas and high participation of their secondary sector in the configuration of the GDP. Additionally, the GRN's topology appeared majorly indifferent to demographic forces, as they are expressed by the population and urbanization variables, showing a contradiction to the gravitational rule describing the spatial transportation models. However, some indirect effects of the population appeared to the GRN's topology through the contribution of the productivity variables. These results illustrated that the GRN is described by a primary developmental functionality bearing out-dated dynamics (i.e. to serve the industrial development that is a prime concern for a country), which generally highlight the deficiency of the infrastructure networks to be adaptive to changes.

Overall, this paper served the interdisciplinary demand in the research field of network science and econophysics, by using the complex network paradigm in spatial and regional analysis, it highlighted the complex relation between network topology and its geographical and socioeconomic framework, it proposed a modeling describing that the volume of the economy affects the network structure and vice-versa, and it provided empirical evidence that topology of a complex network may operate as a socioeconomic index of its real-world framework.

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