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METHODS, TOOLS AND BEST PRACTICES

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The cover image is a photo of a street in the city of Naples during the COVID-19 pandemic quarantine (April 2020)

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Analysis of commuting in Attica

The Attica commuting network

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Abstract

Many complex systems are organized in the form of a network embedded in space. Networks appear naturally in many fields of science and are often inherently complex structures. Many complex networks show signs of modular structure, uncovered by community detection. Communities allow researchers to understand better the network by reducing its complexity. This study analyzes the inter-regional commuting systems of the Attica Region in Greece, employing the approach of detection of complex network communities. In particular, in this paper, the administrative units of Attica are presented as a complex network, using the daily commuting as a criterion for the existence of a functional relationship and the identification of network communities (Functional Urban Areas). Network communities are identified through the modularity maximization method used to analyze complex networks. In parallel with this, through regression model application, the main factors affecting the out-commuting intensity of the municipalities of Attica are defined. The conclusions reached are of special interest to urban planning and especially to Greece, as commuting in this country has not been studied yet extensively.

Keywords

commuting; modularity; Louvain algorithm; network community; regression analysis; Greece.

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1. Introduction

Commuting patterns are determined by -and affect- land use policy and physical planning (De Montis et al., 2010). The network approach has often been adopted to study the mobility patterns between origins and destinations. For commuting analysis, mostly complex network analysis has been used (De Montis et al., 2010). Complex networks are the representation of connections and interactions of real graph-based systems such as social, biological, technological and regional networks (Gach & Hao, 2014). The vertices of the network illustrate the entities of the real graph, while the edges the interactions among them. Recently, the study of complex networks has received a lot of attention from the scientific community.

There are several studies in recent literature, where commuting flows are presented by networks, such as that of Caschili & De Montis (2013) for USA, of De Montis et al. (2013) for Sardinia, of Tsiotas & Polyzos (2013) for Greece and of Pálóczi (2016) for Hungary. Complex networks topologies have interesting properties, such as community structures, which can be used for optimizing policy making. Since networks are used in many different fields to represent the interconnections, e.g. world wide web, biology, transportation, etc., there is big interest in finding optimal ways to cut the graph in smaller components. In particular, urban network communities can be deployed as Functional Urban Areas (FUAs), where Functional Urban Areas in the EU, defined either formally or informally, are statistical spatial units defined primarily with the criterion of commuting flows (Anagnostou, 2017).

Nowadays, commuting -a daily act of a significant part of employees- has been intensified, thus becoming an important part of their everyday life, and has acquired multivariate characteristics, especially after the technological evolution (Polyzos, 2015; Polyzos et al., 2014). Against this background, commuting constitutes a multivariate and dynamic phenomenon and is determined by economic, social and geopolitical factors.

The remainder of this paper is divided into four sections. The next section contains a concise literature review, highlighting the leading attempts to address the importance of network communities, the methods for detecting them, as well as the multivariate character of commuting. In section 3, the data set is described and the empirical analyses are conducted, while section 4 reports the results. The conclusions and references complete and conclude the paper.

2. Literature review

2.1 Network communities

A precise definition of what a network community really is does not exist. One of the most widely accepted and used definitions is that network communities are dense subgraphs of a network where nodes are more often connected with each other, while they are sparsely connected to nodes belonging to different communities (Fig. 1) (Blondel et al., 2008; De Montis et al., 2013; Newman, 2006; Pálóczi, 2016; Porter et al., 2009; Rosvall et al., 2017; Sah et al., 2014). Community is also called cluster or still module (Gach & Hao, 2014). The process of discovering the clusters in the network is known as community detection. Communities summarize the complex network structure, pointing out the main properties of the network in full scale and therefore, they illustrate the dynamics and the general status of the network (Fani & Bagheri, 2017; Hoffmann et al.,2018).

A question that has been raised in recent years is how a given partition of a network into communities can be evaluated. The objective function most widely used for quality optimization of the communities detection in a network due its simplicity is the modularity $Q = \sum(e_{ii} - a_i^2)$. Newman & Girvan (2004) were the ones who worked on it for the first time and it attracted an enormous interest by a large group of researchers (Blondel et al., 2008; Emmons et al., 2016; Fortunato & Castellano, 2009; Newman, 2006; Porter et al., 2009; Rosvall et al., 2017; Sobolevsky et al., 2014; Traag, 2014).

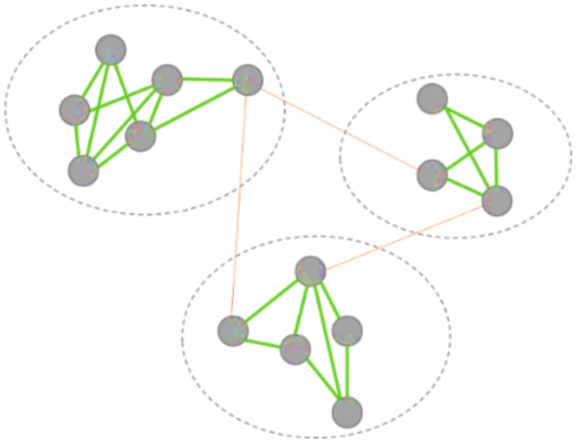


Fig. 1 Community structure example (with dashed line) in a small graph

According to the modularity approach, a subgraph is a community if the number of edges inside the community at a given set of communities is higher than that expected in a random network (null model) (Barthélemy, 2011; Fortunato, 2010; Fortunato & Barthelemy, 2007; Newman, 2004; Nicosia et al., 2009; Raeder & Chawla, 2010; Sobolevsky et al., 2014).

Regarding the choice of the null model, there are several possibilities. The null model mostly used so far has been a random network with the same number of nodes, the same number of edges and the same degree sequence as in the original network, but with the links among nodes randomly placed (Fortunato, 2010; Nicosia et al., 2009). The probability of linking i with j is equal to the product $p_i p_j$ since the edges are placed independently. The result is $k_i k_j / 4m^2$, and finally $p_i = k_i k_j / 2m$ (Fortunato, 2010). The equation of the modularity is the following (1) (Fortunato, 2010; Lambiotte et al., 2009).

$$Q = \frac{1}{2m} \sum_{i.j} [A_{ij} - \frac{k_i k_j}{2m}] \delta(c_i, c_j) \tag{1}$$

where m represents the total number of edges of the network, A_{ij} are the terms of the adjacency matrix of the edges (1 or 0), k_i is the degree of i, c_i is the affiliated community of node i, and function δ (c_i,c_j) is equal to 1 if i and j belong to the same community, i.e. $c_i=c_j$, otherwise zero.

In case of weighted networks, the equation for the modularity is the following (2) (Bagrow, 2007; Blondel et al., 2008; De Montis et al., 2013; Fortunato, 2010; Venkataraman, 2016).

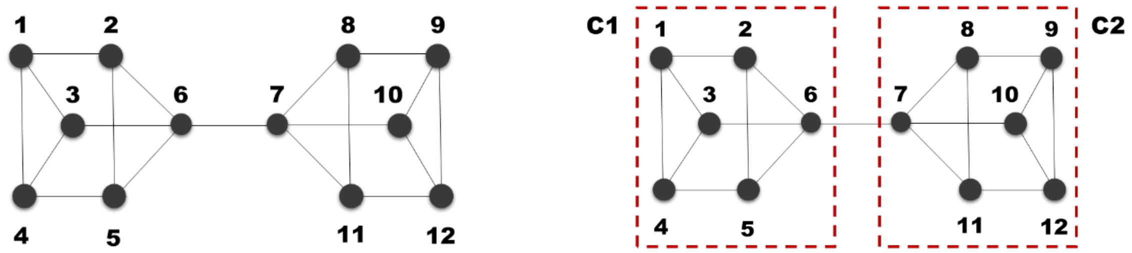
$$Q = \frac{1}{2W} \sum (W_{ij} - \frac{s_i s_j}{2W}) \delta(c_i, c_j) \tag{2}$$

where m is replaced by W which is the sum of the weights of all the edges, W_{ij} is the real weight of the edge ij, and the term s_i represents the node strength and is equal to the sum of the weights of the edges of the node i. The second term in the parenthesis refers to the expected weight of the edge ij in the null model, which is compared with the real weight w_{ij}. c_i is the community in which i belongs and δ (c_i,c_j) function is equal to 1 if $c_i=c_j$, otherwise zero.

This definition of the modularity works for undirected graphs. However, modularity quotation, amended accordingly, also works for directed graphs (Chen, 2015; Lambiotte et al., 2009; Nicosia et al., 2009). Moreover, the modularity does not take into account the spatial effect, but in networks where nodes occupy positions in a Euclidian space, spatial constraints may affect their connectivity patterns.

Q ranges from -1 to 1. If Q values are close to 1, the communities do not exist by chance and they are highly cohesive. On the other hand, a partition where all the vertices are grouped into the same community has a modularity equal to zero. Therefore, the value of 0 indicates a single cohesive community for the whole graph, while the negative values imply the absence of real communities.

For better understanding of the above, examples of calculating the modularity in a non-weighted and in a weighted network follow. Suppose there is a network G with 12 nodes and 19 undirected edges. Let A (Tab. 1) be the adjacency matrix of the network G with 12 nodes, where the element $A_{ij}=1$ denotes that there is an edge from node i to node j. C1 and C2 represent the two initial communities. The calculations of the Q_{11}, Q_{12}, Q_{13} indicatively follow, as well as the modularity Q matrix (Tab. 2) where all of the Q values for this separation are included. The value of total network modularity when this is separated in C1 and C2 is equal to 0.44.



(a) (b)

Fig. 2 (a) Example of modularity calculation of a network G and (b) separation in communities C1 and C2

Nodes	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	1	1	1	0	0	0	0	0	0	0	0
2	1	0	1	0	1	1	0	0	0	0	0	0
3	1	0	0	1	0	1	0	0	0	0	0	0
4	1	0	1	0	1	0	0	0	0	0	0	0
5	0	1	0	1	0	1	0	0	0	0	0	0
6	0	1	1	0	1	0	1	0	0	0	0	0
7	0	0	0	0	0	1	0	1	0	1	1	0
8	0	0	0	0	0	0	1	0	1	0	1	0
9	0	0	0	0	0	0	0	1	0	1	0	1
10	0	0	0	0	0	0	1	0	1	0	0	1
11	0	0	0	0	0	0	1	1	0	0	0	1
12	0	0	0	0	0	0	0	0	1	1	1	0

Tab.1 Adjacency matrix of the example network G

$$Q_{11} = A_{11} - \frac{k_1 k_1}{2m} = 0 - \frac{3 \times 3}{2 \times 19} = -0.24$$

$$Q_{12} = A_{12} - \frac{k_1 k_2}{2m} = 1 - \frac{3 \times 3}{2 \times 19} = 0.76$$

$$Q_{13} = A_{11} - \frac{k_1 k_3}{2m} = 1 - \frac{3 \times 3}{2 \times 19} = 0.76$$

Nodes	1	2	3	4	5	6	7	8	9	10	11	12
1	-0.24	0.76	0.76	0.76	-0.24	-0.32	0	0	0	0	0	0
2	0.76	-0.24	-0.24	-0.24	0.76	0.68	0	0	0	0	0	0
3	0.76	-0.24	-0.24	0.76	-0.24	0.68	0	0	0	0	0	0
4	0.76	-0.24	0.76	-0.24	0.76	-0.32	0	0	0	0	0	0
5	-0.24	0.76	-0.24	0.76	-0.24	0.68	0	0	0	0	0	0
6	-0.32	0.68	0.68	-0.32	0.68	-0.42	0	0	0	0	0	0
7	0	0	0	0	0	0	-0.42	0.68	-0.32	0.68	0.68	-0.32
8	0	0	0	0	0	0	0.68	-0.24	0.76	-0.24	0.76	-0.24
9	0	0	0	0	0	0	-0.32	0.76	-0.24	0.76	-0.24	0.76
10	0	0	0	0	0	0	0.68	-0.24	0.76	-0.24	-0.24	0.76
11	0	0	0	0	0	0	0.68	0.76	-0.24	-0.24	-0.24	0.76
12	0	0	0	0	0	0	-0.32	-0.24	0.76	0.76	0.76	-0.24

Tab.2 Modularity Q matrix for the separation of G in communities C1 and C2

So, $Q = \frac{\sum_{ij} Q_{ij}}{2m} = \frac{16.76}{2\times 19} = 0.44$

At the second step, the separation in communities is modified accordingly to Fig. 3. Since the separation changes, the total value of Q will change as well. For this reason, it is recalculated. Tab. 3 is the new modularity Q matrix for separation of network in communities C1, C2, C3 and C4. The new modularity value for the whole network is 0.38. Therefore, both separations in communities are acceptable, as Q value is higher than 1, but the first separation is considered better than the second one since the modularity has a higher value.

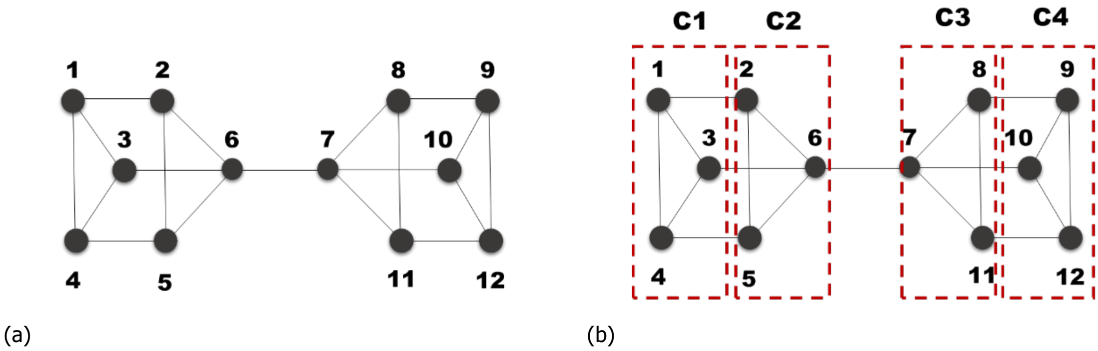


Fig. 3 (a) Example of modularity calculation of a network G and (b) separation in communities C1, C2, C3 and C4

Nodes	1	2	3	4	5	6	7	8	9	10	11	12
1	-0.24	0	0.76	0.76	0	0	0	0	0	0	0	0
2	0	-0.24	0	0	0.76	0.68	0	0	0	0	0	0
3	0.76	0	-0.24	0.76	0	0	0	0	0	0	0	0
4	0.76	0	0.76	-0.24	0	0	0	0	0	0	0	0
5	0	0.76	0	0	-0.24	0.68	0	0	0	0	0	0
6	0	0.68	0	0	0.68	-0.42	0	0	0	0	0	0
7	0	0	0	0	0	0	-0.42	0.68	0	0	0.68	0
8	0	0	0	0	0	0	0.68	-0.24	0	0	0.76	0
9	0	0	0	0	0	0	0	0	-0.24	0.76	0	0.76
10	0	0	0	0	0	0	0	0	0.76	-0.24	0	0.76
11	0	0	0	0	0	0	0.68	0.76	0	0	-0.24	0
12	0	0	0	0	0	0	0	0	0.76	0.76	0	-0.24

Tab.3 Modularity matrix for the separation of G in communities C1, C2, C3 and C4

So, $Q = \frac{\sum_{ij} Q_{ij}}{2m} = \frac{14{,}36}{2\times 19} = 0.38$

Although modularity optimization is the most popular method for detecting communities (Fortunato & Barthelemy, 2007), it has been proven in recent years that the modularity also has some drawbacks (Emmons et al. 2016; Sobolevsky et al. 2014). The main drawback of the modularity is considered to be the resolution limit, which means that modularity does not allow the detection of relatively small communities in large networks (Traag et al., 2013). Besides this, the approach of modularity optimization is not satisfactory when the network is hierarchically modular and is composed of partitions at different scales. Furthermore, the modularity has been proven sensitive to individual connections, which means that if two sub-graphs are linked with some false edges, the modularity will merge them into the same community, assuming a relationship that actually does not exist (Fortunato 2010).

Moreover, the traditional methods based on modularity optimization do not allow overlaps among communities, which means that each vertex can be placed into just one community, although real networks are almost never divided into sharp subnetworks (Fortunato 2010; Nicosia et al., 2009). Finally, it is common for the detection of communities to not take into account the direction of the edges and to consider the graph as non-directional, which could bring misleading results (Fortunato, 2010).

The problem of modularity optimization is NP-complete (Gach & Hao, 2014). Different algorithms are able to find a good approximation of maximum modularity Q. One has to take many factors into account when choosing an algorithm to use. In many cases, a compromise must be reached between accuracy and running time, especially for larger networks. In an attempt to improve Moreno's sociogram (1934), one of the first algorithms for community detection was introduced -the adjacency matrix by Forsyth et al. (1946). However, the initial methods were efficient just for small networks where data were collected by the researchers themselves, and not for the large networks of today, where the data are not collected personally by the researchers (Lee & Cunningham 2013). Distributive algorithms that start from the entire network and break it, agglomerative algorithms which merge similar nodes / communities in a repetitive process, and optimization methods which maximize an objective function have been developed (Blondel et al., 2008, De Montis et al., 2013, Newman & Girvan, 2004; Sobolevsky et al., 2014; Venkataraman, 2016).

In a comparison of algorithms used to optimize the modularity and the division in communities by Sobolevsky et al. (2014), the Louvain method was found to be a good method overall, i.e. in terms of computation time and accuracy (Fig. 4). In particular, Louvain is a greedy agglomerative hierarchical algorithm proposed by Blondel et al. (2008). Two phases are repeated iteratively until a local maximum of the modularity is obtained (Fig. 5).

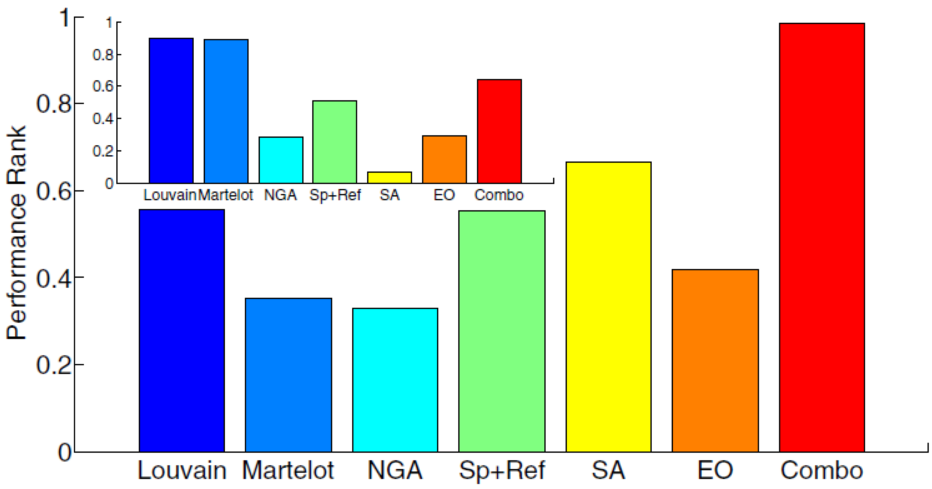


Fig. 4 Average normalized performance rank of each algorithm in terms of partitioning quality (big chart) and speed (small chart)

During the first phase, each vertex is placed into a separate community and therefore, the initial partition is composed of N singleton communities. Then, the modularity gain of moving a node i from its community to the community of one of its neighbors j is found. If the gain is positive, v_i is transferred to the v_j community, otherwise v_i remains in its original community. This process is applied repeatedly and sequentially for all nodes until no individual move can improve the modularity. The first phase is then finished. During the second phase, all of the communities found in the earlier phase are treated as nodes of a new network and the weight of links is found. The new resulting weighted network is then submitted to the first phase and this process is iterated again and again (Blondel et al. 2008; Venkataraman 2016).

The fact that whenever no more changes can be made by moving nodes, algorithm aggregates the graph and reruns, makes it work yet well and so fast (Traag, 2014). The algorithm provides a hierarchy of communities produced at each pass of the algorithm, as communities within communities are built during the process.

Nevertheless, some drawbacks of the Louvain algorithm are mentioned in the literature. First of all, it may lump fine-grained cohesive subgraphs together (Suthers, 2017). In particular, Traag et al. (2019) who created the new Leiden algorithm, point out that although the algorithm, when finalizing the process, guarantees that communities cannot be merged further and that no other nodes can be moved to communities, it may end up with communities in which there are unconnected or poorly connected sub-communities. For example, as shown in Fig. 6, node 0 entered the pink community and constitutes the link between 1-2-3 and 4-5-6. In the next step, however, when node 0 moves to another community and stays there, the pink community will remain as it is, and essentially consists of two unrelated communities. The extreme scenario is that communities are totally unrelated. The common scenario is to have just a few connections (Traag et al., 2019).

Finally, the results of Louvain algorithm are affected by the order in which the nodes are taken for merger in the first phase of the run (Chen, 2015).

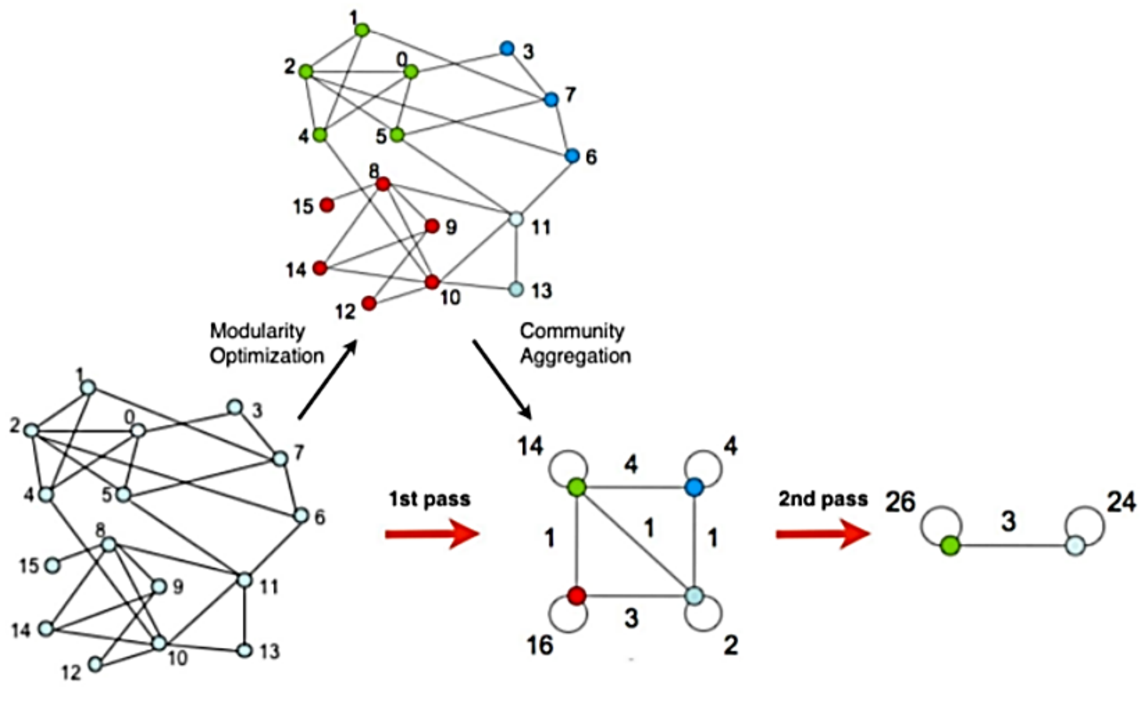


Fig. 5 Louvain algorithm steps

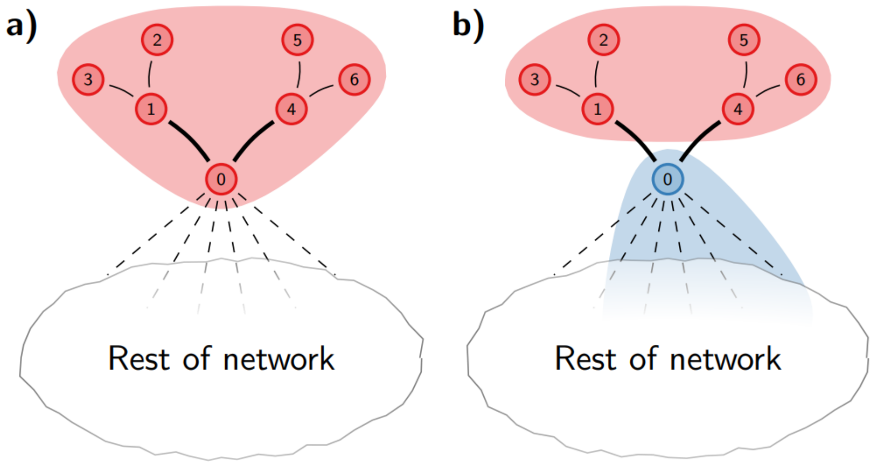


Fig. 6 Possible error of the Louvain algorithm

2.2 Commuting intensity analysis

The term commuting refers to the habitual daily act of leaving one's home and traveling to work beyond the territorial unit of residence (Polyzos, 2015; Stefanouli & Economou, 2019; Stefanouli & Polyzos, 2015a; Stefanouli & Polyzos, 2015b; Stefanouli & Polyzos, 2017; Tsiotas & Polyzos, 2013; Van der Laan & Schalke, 2001). This type of movement is considered to be non-elastic in comparison to other types of movement, such as for shopping, for entertainment, etc.

Except for identifying the structure of commuting, in regard to defining administrative boundaries on a scientific basis, it is necessary to define the factors at play in commuting intensity at an earlier stage. In literature, many variables have already been used in order to better understand commuting behavior. Some of the variables have to do with the characteristics of the commuting region, while the rest of them with personal characteristics of the commuter. Specifically, there are studies proving the dependence of commuting intensity from the commuter sex, job position, age, marital status, education, etc., while there is also dependence between commuting and factors like GDP, unemployment, population, land use, and so on.

3. Data and Methodology

The study area of this paper is the Greek Region "Attica", as shown on the map in Fig.7, where all of the thirteen Greek Administrative Units are illustrated. Attica is the biggest Administrative Unit in Greece in terms of population. In particular, Attica's population is equal to 3.828.434, while the total Greek population is 10.816.286 (according to data from 2011). During the decades of the 1980s, 1990s and 2000s, there was an urban sprawl combined with a rapidly developing private housing market (Sayas, 2006). At that time, many distant areas were transformed from "vacation" to residential ones (Sayas, 2006). Athens -part of Attica- is the capital of Greece, and for this reason, it is the location of many large companies' headquarters and the tertiary sector is highly developed. This fact, combined with the large population, leads to a very large workforce. However, the unemployment rate is at the same level as for the other Regions. There are areas in Attica that are almost exclusively residential or commercial, but most of the areas have mixed uses, which increases the commuting intensity. Moreover, Attica is currently the only Region with urban rail transit, such as overground train, underground train and tram. In addition to this, the movements are spread throughout the day and not only during peak hours. On the other hand, Attica is the smallest Administrative Unit in terms of area (km^2).

Fig. 7 A general view of the Administrative Regions of Greece (Attica is shaded in dark green)

Attica	
Population (2011)	3,828,434
Population of foreign nationals (2011)	405,831
Area (km2)	3,807
Area occupied by the locality (buildings, roads, etc.) (km2)	543
Per capita GDP (2011)	25,380 euros
Gross value added by tertiary sector	78,843 million euros
Unemployment (2011)	19%
Cars for private use (2011)	2,745,727

Tab.4 Socio-economic indicators of Attica

In choosing only the Region of Attica for analysis in this paper, rather than the whole country, the study of Stefanouli and Polyzos (2018) played a role, given that as found therein, the commuting communities of Greece were delineated and, in terms of the low hierarchical level, Attica was the only Region that was subdivided much further in communities, in contrast to the rest of the Administrative Units. This proves that Attica is of much more interest compared to the rest of the Regions. Tab. 4 shows some indicative socio-economic indicators of Attica.

In the present paper, Functional Urban Areas of the Region of Attica are defined by complex network analysis and in particular, by community detection based on commuting flows, as discussed in the previous section.

For the application, the commuting data of the administrative units "Municipalities of Attica" -derived from the General Population Census 2011 in Greece- are used. The data are courtesy of the Hellenic Statistical Authority (ELSTAT). The geographical level at which commuting data are used here is that of municipalities. The nodes of the network correspond to the municipalities -places of residence/work- while the edges of the network represent the commuting flows. The commuting data of Attica commuters were entered into a double-entry matrix after the following modifications:

- Trips of people who live and work in the same area are not considered in this study, and for this reason, the values of the matrix diagonal are zero;
- The commuting data referring to movements without a permanent destination or with destination abroad are not subject to study;
- The commuting movements with duration longer than 120min were removed since it is considered not to be on a daily basis;
- The island municipalities are not studied since it is considered that workers' movements are not on a daily basis;
- The municipality of Trizinia was removed from data as an outlier due to the long distance from most of the Attica municipalities.

After applying the above constraints, the nodes of the network are 59 in total, which correspond to the set of Attica municipalities, while the total edges are 3,238, which correspond to the pattern of commuter exchanges among those municipalities. The largest number of edges belongs to the Municipality of Athens.
Before the detection of communities, analysis of the main factors affecting the out-commuting distance of the Attica's commuters is carried out. In Tab. 5 the dependent and independent variables used in the analysis are presented.
First and foremost, it should be stressed that for the examined period of time in Greece -close to the year 2011- due to the economic recession, there is a drop of average annual income which simultaneously causes a drop in transport expenditure from average € 500 to € 300 per year (Stamos et al., 2016). For the same reason, the average traffic flow was reduced (Stamos et al., 2016). Fig. 8 shows the average traffic flow in the Attica Region, where the reduction of urban traffic flows is obvious. In the light of these facts, the commuting flows in the Region of Attica could not have been left unaffected.

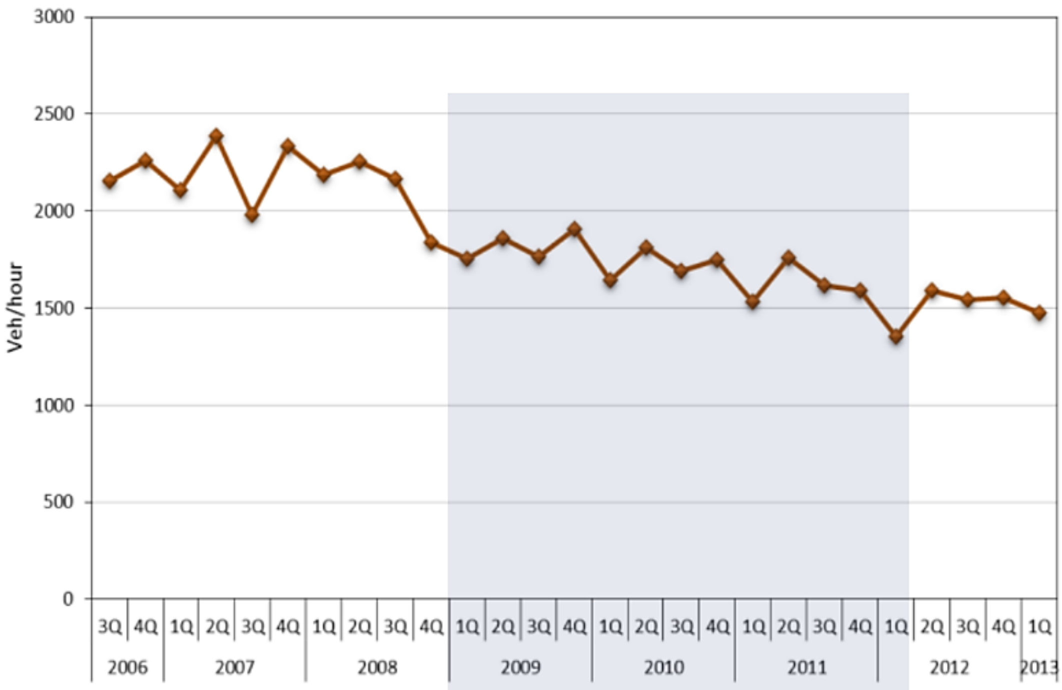


Fig. 8 Average traffic volume in Attica

Variable	Symbol	Description	Measure	Primary data source and year
Out-Commuting distance	Y	Weighted average out-commuting Euclidean distance of an Attica municipality	km	EL.STAT., (2011) & Google maps (2019)
Population density	X1	Population density of the Attica municipality	Number of citizens / Area (km2)	EL.STAT., (2011)
Job-housing ratio	X2	The ratio between job positions and residences of the Attica municipality	Number of Employees / Number of Residences	EL.STAT., (2011)
Business density	X3	Business density of the Attica municipality	Number of Businesses / Population	EL.STAT., (2015)
Participation of the tertiary sector businesses	X4	Participation of the tertiary sector businesses in the Attica municipality	Percentage of tertiary sector businesses out of the total number of businesses	EL.STAT., (2015)
Educational level	X5	Number of people of the Attica municipality with bachelor's degree or above	Percentage of citizens with undergraduate degree	EL.STAT., (2011)
Immigrant density	X6	Immigrant density of the Attica municipality	Number of immigrants / Area (km2)	EL.STAT., (2011)
Unemployment	X7	Number of registered unemployed of the Attica municipality	Percentage of unemployed citizens	EL.STAT., (2011)

Tab.5 Definition of variables and data sources

In the present analysis, the commuting distance is calculated as the one-way Euclidean distance between the coordinates of home municipality and work municipality. Thus, it does not measure the actual distance, which is about 30 percent longer (Sandow, 2011), or the commuting time. Euclidean distance was chosen because it is a static and neutral measure of distance and it was considered more appropriate in this case since commuting road distance, as well as commuting time, in Attica varies a lot depending on the hour of the day, the means of transport, etc.

The independent variables were chosen for the analysis based on the literature. At first, the density of population, interpreted as a measure of how urbanised the municipality is, has been found to be related to out-commuting intensity. Specifically, the more populous areas experience commuting within the spatial unit, resulting in less movements away from the unit and in shorter out-commuting distance (Antipova et al., 2011; Polyzos et al., 2014; Susilo & Maat, 2007).

In parallel with population density, residence density as well as business density are used as indications of the commercial/office or the residential land type of a municipality. It is expected that municipalities with an equilibrium of job positions and dwellings would have lower commuting intensity, but it is unknown if it affects the out-commuting distance. According to Moeinaddini et al. (2012), job-housing balance can reduce out-commuting at city level. In addition to this, the variable percentage of tertiary sector businesses is used, because it is considered that these businesses have a higher pull effect, leading to higher commuting distance too.

Regarding educational level, it has most probably a positive relation with the out-commuting distance. However, Antipove et al. (2011) found a non-significance of educational attainment in commuting behavior (Polyzos et al., 2013; Shoag & Muehlegger, 2015). Moreover, nationality is a factor in the concept since the usual discrimination in finding a job, as well as the marginalisation in specific districts of the city, may affect how far they commute in order to have a job (Antipova et al., 2011; Östh & Lindgren, 2012). Finally, unemployment is deemed noteworthy since the unemployed are usually willing to travel longer distances in order to work (Östh & Lindgren, 2012; Polyzos et al., 2013).

For the above described analysis of the average out-commuting distance, a linear regression model is chosen. After the first runs of linear regression models and the design of diagrams dependent -independent for all pairs of variables- it was found that the relation is not linear, so transformation of some or all variables is required. Finally, the model with the highest adjusted R^2 is chosen.

The detection of communities follows the regression analysis. The research for communities detection was made using the Gephi Graph Visualization and Manipulation open source software (v.0.9.2) which enables the use of Louvain algorithm. Gephi is developed in Java and is an open source software for network and graph analysis and visualization. It is a platform for exploration, visualization, analysis, spatial mapping, filtering and management for all types of networks (Bastian et al., 2009; Flores De La Mota & Huerta-Barrientos, 2017; Ji et al., 2015, Pavlopoulos et al., 2017; Venkataraman, 2016).

Since in weighted networks the clusters are defined not only by the topology but also by the weights of the edges, in this paper the weighted commuting network has been chosen for analysis, by giving each link a weight representing the number of commuters that flow through that connection.

Although the proposed way is that the vertices are examined in a purely random order during each iteration, the parameter "randomize" was not checked at the end, because the trials with this option checked gave many similar but slightly different results, so that no clear choice could be made.

The Louvain algorithm in Gephi accepts a resolution parameter that determines how coarse the individual communities it detects will be. The default resolution value is 1, while lower resolution values correspond to lower hierarchy levels with more communities detected. The resolution parameter was chosen after trial runs, so that the modularity value does not decrease and the number of arising communities is adequate for analyzing their properties. The default resolution value 1 produced just two communities, which did not allow the analysis of communities. Therefore, a lower hierarchy level with a lower resolution value was required for the analysis. Testing a number of different resolution settings, a resolution parameter of 0.5 in Gephi produced a set of communities that would be adequate for analysis without decreasing a lot the modularity value. It should be noted that at every level examined, the modularity value was quite low and slightly different. This is probably because the communities of Attica are not very clearly separated.

4. Results and Discussion

4.1 Results of regression analysis

Firstly, the results of the regression analysis are presented. As was mentioned above, the relation of dependent - independent variables was not found to be linear. Therefore, the variables were transformed in order to find the linear model with the best fitting, using also the residual plots as a guide since with multiple predictors a single scatterplot is not adequate.

Before the analysis, the bivariate correlations of the independent variables were checked so that no significantly correlated independent variables are used at the same regression model. The following numerous pairs of variables were found to be significantly correlated at 0.05 level: population density - immigration density, population density - participation of the tertiary sector businesses, business density - educational level, business density - unemployment, job-housing ratio - educational level, job-housing ratio - participation of the tertiary sector businesses, educational level - unemployment, educational level - participation of the tertiary sector businesses, immigration density - participation of the tertiary sector businesses, and unemployment - participation of the tertiary sector businesses.

After using a "trial and error" approach, the model with structure $Y = X1 * X2 * Xn$ was found to be the most appropriate, where the transformation both of the predictors X and the response Y values were required.

However, at each of the runs not all of the independent variables were found to be statistically significant and not all of them demanded the same type of transformation. Finally, the two following models were found to have the best fitting (Equations 3 and 4).

The first model has dependent variable the out-commuting distance and predictors the business density, the job-housing ratio and the immigration density, while the second model has dependent variable the out-commuting distance and predictors the population density and the job-housing ratio. As it is obvious, log transformation was required to make the model linear for regression analysis.

$$\begin{gathered} \textit{Model}\ 1\text{: Out} - \text{commuting distance} = \\ 2.83 * \text{business density}^{2.8} \ * \ \text{job} - \text{housing ratio}^{-1.38} * \mathrm{e}^{-0.4*\text{immigration density}} \end{gathered} \tag{3}$$

$$\begin{gathered} \textit{Model}\ 2\text{: Out} - \text{commuting distance} = \\ \text{population density}^{-0.393} \ * \ \text{job} - \text{housing ratio}^{-5.174} * \mathrm{e}^{2.908*\text{job}-\text{housing ratio}} \end{gathered} \tag{4}$$

Model	R Square	Adjusted R Square	Durbin-Watson
1	0.806	0.795	1.78
2	0.830	0.821	1.75

Model 1	**Sig**
Constant	0.000
ln (business_density)	0.030
ln (job-housing ratio)	0.000
Immigration density	0.000
Model 2	**Sig**
Constant	0.499
ln (population density)	0.000
ln (job-housing ratio)	0.002
job-housing ratio	0.010

Tab.6 Goodness of fit statistics

According to the two regression models, it seems that the increase in population density leads to a decrease of the out-commuting distance. A high population density may be the result of great number of residents in an area of medium size, or of a normal number of residents in an area of small size. The latter is expected to result in a small out-commuting since the nearby areas are closer. The same relation applies to the predictor immigration density, which was expected because immigrants usually do not commute long distances. In the same vein, increase of the job-housing ratio results in a decrease of the out-commuting distance, which stands to reason because the higher the offer of job positions in comparison with housing in an area, the more residents will find a job inside that area. On the other hand, the more business density increases, the more out-commuting distance increases too, which cannot be justified according literature thus far.

According to the above results, a few comments and proposals follow. Taken as a given that the out-commuting distance should be kept at a moderate level for economic, environmental, social and even psychological reasons, based on the results, the land uses in every area should be mixed and kept in balance, so that the employees are able to find a job-position quite close to their residence. In parallel with this, the relation between the immigration density and the out-commuting distance indicates the inability of immigrants to have a job far from their residence. This may lead to further problems of exclusion with a significant social impact. Besides this, these results also indicate possible insufficiency of public transportation since immigrants use mainly public transportation for their daily travel. A modal split analysis made for Thessaloniki's agglomeration located in northern Greece proves that the majority of trips is conducted with private vehicles

(67% private cars, 4% motorcycles and 4% taxis), which reveals a potential insufficiency of public transportation too (Mitsakis et al., 2013). There are studies that prove that in more society-centered countries, such as France and Switzerland, investments in public transportation have improved the accessibility of disadvantaged groups (Pojani, 2011). Therefore, transport inequalities should be reduced through transport planning with social inclusion policies.

4.2 Results of network analysis

The second step of the analysis has to do with the detection of commuting network communities of Attica. The basic metrics of the network examined are summarized in Tab. 7. The very low average path length value, when compared to the number of nodes, indicates small-world properties, which characterize networks with a high clustering coefficient and a small characteristic path length (Mehlhorn & Schreiber, 2013). The following table also shows the modularity value, as well as details about the detected communities, resulting from the optimization running the Louvain algorithm as described in the previous section. As it is shown, the modularity value is 0.098. It has already been highlighted that the communities do not seem to be very stable. In total, 11 communities were found as they are presented in Fig. 9. The Geo Layout algorithm is used for a better visualization of the graph since the nodes of the network represent the Municipalities and their relative geographical position can justify the existing intense or non-intense commuting flows.

Statistical Metric	**Attica Network**
Average Degree	55.79
Average Weighted Degree	13,718.03
Network Diameter	2
Average Path length	1.02
Communities	
Modularity (resolution=0.5)	0.098
Average number of nodes	5.3
Max number of nodes	9
Min number of nodes	2

Tab.7 Metrics of the examined network

Based on the results, the method detected communities of continuous spatially municipalities and with interrelations that can be interpreted. A strong dependence between the central area of Athens and the periphery is obvious, together with the number of flows dense moving from the periphery to the center.

As already mentioned, the dividing into communities is not so clear and this may be due to various reasons. First of all, in Attica there are business districts in many municipalities and not only in the center. Moreover, there is a quite dense urban rail transit network which connects specific areas (Fig. 10). A kind of correlation between the two maps is distinguished, but it is not so significant. The central communities have a smaller radius in comparison with the remote ones. For understanding the communities better, the Gini index is calculated for each one of the communities as a measure of inequality regarding the population, the residences and the businesses. The Gini index is used mostly in the distribution of income although its applications are not limited to income distributions. According to Gini's Mean Difference Approach, the equation of Gini index can be defined as the following one (Eq. 5) (Xu, 2004):

$$G = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}|X_i - X_j| \tag{5}$$

Where X is the variable under study of communities i, μ is the average of the variable X and n is the number of the communities under study. The results of Gini indexes are shown in Tab. 8. Since a Gini coefficient of zero expresses perfect equality, based on the above results, the detected communities in Attica are not equal, in regard to population, residences and businesses. It is interesting that for all of the three examined factors, Gini index value is approximately 0.35 – 0.4, which may mean that these factors of a community are correlated.

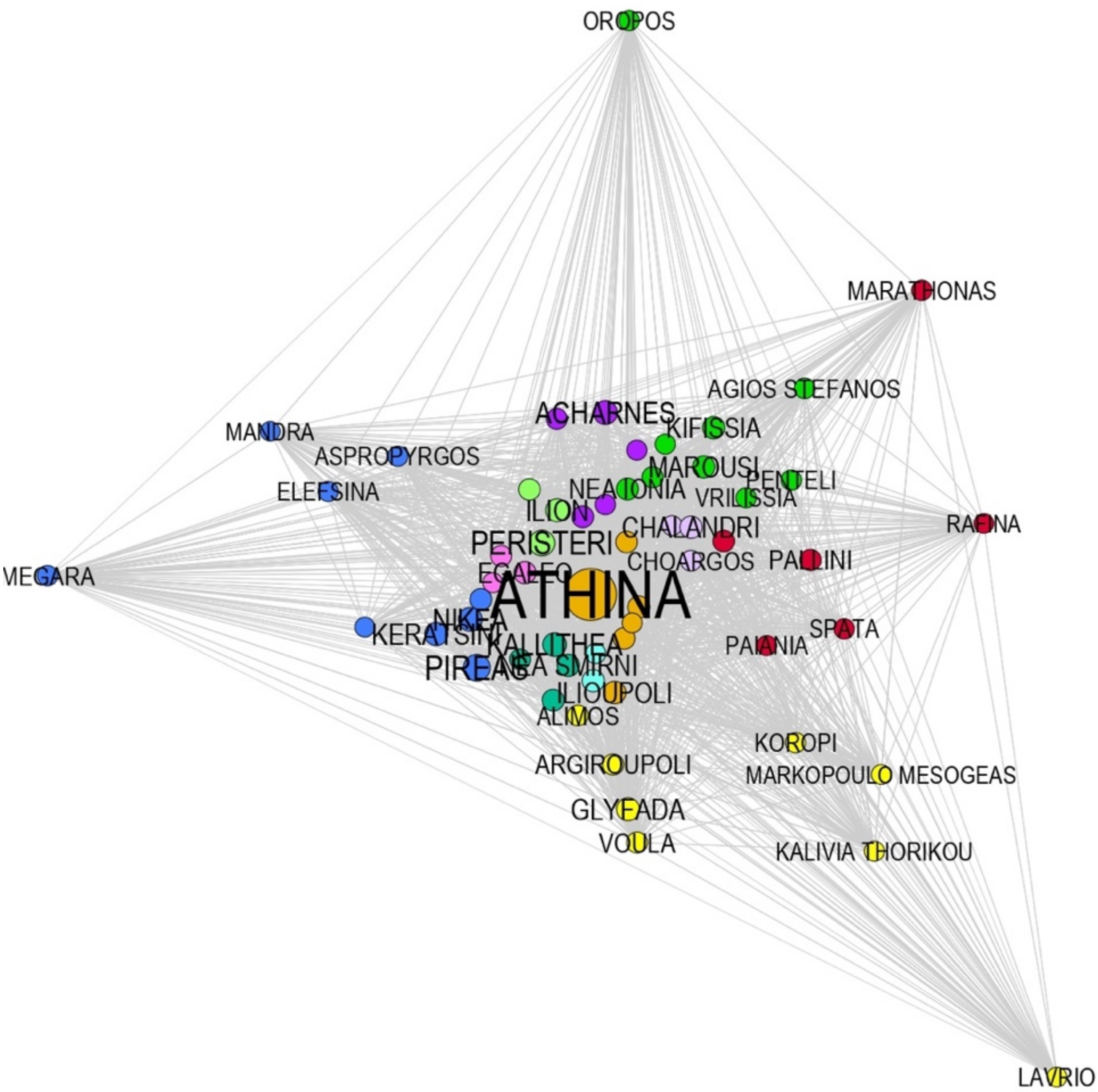


Fig. 9 The detected commuting network communities of Attica

Gini index category	Value
Population	0.34
Residences	0.37
Businesses	0.40

Tab.8 Results of Gini index of the communities

Fig. 10 Urban rail transit network in Attica

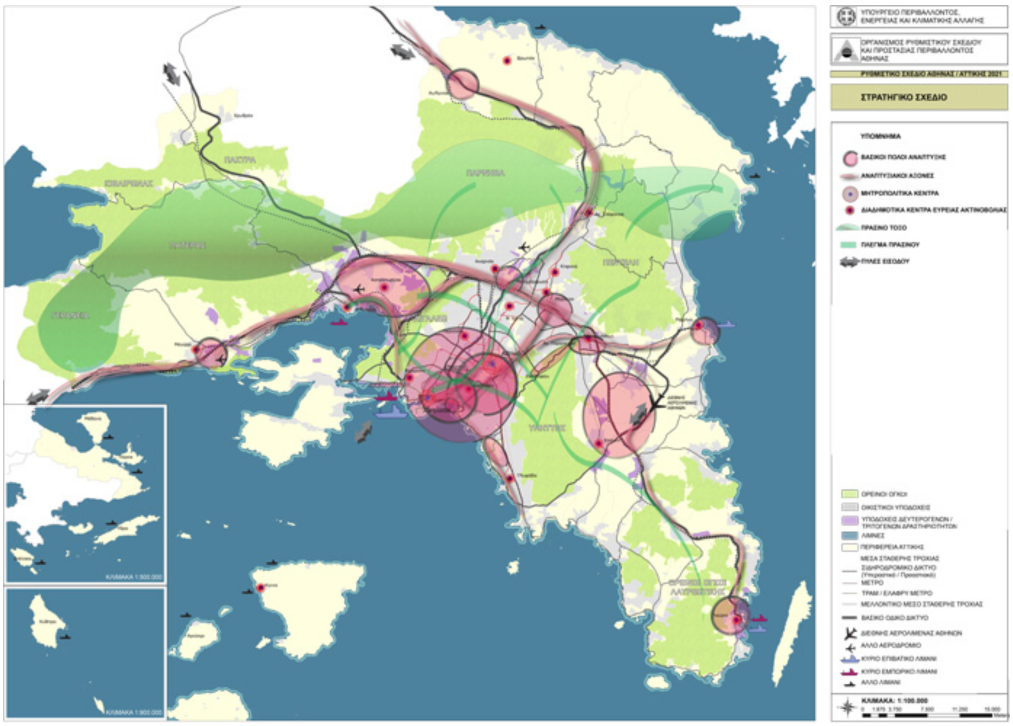


Fig. 11 Regulatory Plan of Attica 2021

In parallel with the rail transit network, it is interesting to collate the network communities found with the "Regulatory Plan of Attica 2021" which is in effect since 2014 (law 4277/2014) (Fig. 11). There are similarities between the communities and the development poles of the plan, which included also development axes along the main road network and did not focus on stimulating the centrality (Triantis, 2017).

5. Conclusions

This article initially studied the identification of spatial units and the use of network analysis for this purpose. Thereafter, the methods for network community detection were described, with a special focus on that of modularity optimization and mainly with the use of Louvain algorithm. Beside this, some of the main factors affecting the commuting distance were presented and through regression analysis, their relationship with the out-commuting distance of the municipalities of Attica was found. Finally, the commuting communities of Attica were found.

The methodology used for communities detection in this paper is based on network analysis, which contributes to uncovering complex phenomena by using a limited set of variables that show the collective features of commuting systems. It is clear that communities are frequently present in networks. Detection of communities helps to uncover a priori more or less unknown functional modules. There is the need for such flexible and efficient methodologies, which integrate the special characteristics of local communities, for applying urban policies. Defining communities in a consistent and functional way, like with the use of commuting flows in a network structure, contributes to solving the urban problems in the suitable scale, as well as making policy interventions on the suitable urban hierarchical level, in order to receive immediate results.

A thorough investigation of commuting communities can predict the future sustainability of a project and justify efforts towards a certain direction. Moreover, they can be used as a guidance to planners and stakeholders, whose conceptions diverge, when planning and implementing new measures. After the recent end of financial crisis in Greece, there is pressure from economic and technocratic networks for achieving development goals, where spatial planning plays a significant role as well.

Furthermore, the regression analysis revealed that the population density, as well as the density of job-positions, in general play a significant role in the commuting distance. Planners and decision makers should tackle those complex commuter issues which have an impact on the landscape and on the land uses of Attica. Besides this, they could use it for mapping a sufficient and sustainable urban transportation network. Finally, future trends in commuting flows could be revealed, given the future changes in land use, population, etc.

The analysis in this paper may provide a reference for future comparisons in this study area by applying the methodology, with necessary modifications, to other data sets. Moreover, in the context of this paper, the impact of the commuting on the land uses and the landscape of Attica has not been examined, which would be interesting to be included in a future extension. Besides this, the possibility of overlapping communities could also be studied. Furthermore, the quality function used for optimization, besides the basic information about the network structure, could also include other information, such as node characteristics, distance between them, etc. Moreover, some of the above ambiguous results, like insignificant predictors, call for more empirical studies, as well as more convincing theories to untangle the complex interaction between a range of factors and commuting outcomes. Beside this, further research should focus on lower spatial hierarchical units. Concluding, commuting proves to be an important and even determinative factor in urban planning at the local level.

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Image Sources

Fig. 1: Stefanouli & Polyzos, 2018

Fig. 2: Author

Fig. 3: Author

Fig. 4: Sobolevsky et al. 2014

Fig. 5: Blondel et al., 2008

Fig. 6: Traag et al., 2019

Fig. 7: Author

Fig. 8: Stamos et al., 2016

Fig. 9: Author

Fig. 10: Wikipedia.org, edited by author

Fig. 11: Triantis, 2017

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