

## **A COMBINED GRAPH THEORETIC AND TRANSPORT PLANNING FRAMEWORK FOR THE ECONOMIC AND FUNCTIONAL ANALYSIS OF LARGE-SCALE ROAD NETWORKS**

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### **Abstract**

Road networks are the backbone of our society and a built capital enabling the movement of people and transportation of goods. Their design should comply with both traffic and technical requirements and economic demand, to ensure efficient connectivity, accessibility, optimum resource allocation, and long-term sustainability. Poised on the intersection of this bi-dimensional context, this paper develops a methodological framework incorporating these two dimensions in road network analysis to evaluate both functional and economic aspects of the network. Within this framework, we incorporate functional and economic information into an interurban road graph model constructed on empirical data from Greece, and we afterward evaluate the level of determination and the model's applicability and usefulness in transportation planning. Overall, our findings reveal the proposed approach capable of evaluating potential interventions in the network and estimating traffic volumes, especially in data-constrained situations. In empirical terms, they indicate that the socio-economic performance of the national road network is satisfactory, albeit not fully optimized.

**Keywords:** Graph theory, Road networks, Traffic assignment, Economic performance, Functional performance

**JEL classification:** R41, R42

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## **Introduction**

The transportation sector plays a pivotal role in modern society, and it is quite often described as its “blood system” (Banister et al., 2011). Just as the circulatory system ensures the distribution of vital nutrients to all parts of the body (Abeyrathne and Lanel, 2021), transportation networks facilitate the movement of people (Tsiotas and Tselios, 2022), goods (Hesse and Rodrigue, 2004; Nijkamp et al., 2004), and information (Barthelemy, 2011; Rodrigue et al., 2013), enabling economic and social interactions (Tsekeris and Stathopoulos, 2006; Capello, 2016; Polyzos and Tsiotas, 2020), as well as cultural exchanges on various geographical scales. Hence, the design of an effective transportation network has always been a great challenge (Tsiotas and Polyzos, 2024) for engineers and transportation decision makers. This stems from the need to meet a broad spectrum of demanding requirements that frequently conflict as well. Their design should comply with both traffic (McNally, 2007; Ahmed, 2012; Galib et al., 2014) and capacity requirements (Liu et al., 2017) and economic demand (Polyzos and Tsiotas, 2023), to ensure efficient connectivity, accessibility (Kondo, 2011), optimum resource allocation (Feng and Hsieh, 2009) and long-term sustainability (Roth and Kåberger, 2002).

Within this context, the scope of this paper is to provide an integrated methodological framework for evaluating both functional and economical dimensions of road networks. This can be achieved through the use of the network paradigm (Newman, 2010; Barabasi, 2013) and the results obtained from traffic assignment models (Matheu, 2011; Saw et al., 2015; Boyles et al., 2020), having as main goal to shape new indicators that provide a more comprehensive and realistic understanding of the network’s characteristics and its interaction with surrounding socio-economic systems. Through the lens of graph theory (Rodrigue et al., 2013; Anderson and Dragičević, 2020), a transport network is conceptualized and analyzed as a graph, with nodes representing points and edges indicating connections among them (Tsiotas, 2021; Tsiotas and Polyzos, 2024). This approach allows for an investigation of the topological and geometrical characteristics of the network, enabling the identification of optimal routes for connecting various regions within the transportation system (Tsiotas, 2021). On the other hand, adhering to the principles of classical transport planning (McNally, 2007; Yao et al., 2008; Ahmed, 2012), introduces additional dimensions to the network analysis, incorporating parameters such as traffic demand and traffic assignment. This approach offers a more realistic understanding of the dynamic and behavioral characteristics of the network. By integrating both approaches, this study endeavors to provide valuable insights into the complex interplay between transportation infrastructure and socio-economic dynamics.

The structure of the paper is as follows. Section 2 provides the theoretical background of the study, including a topological analysis of transport networks, the structural characteristics of road networks, the urban transport planning framework, the fundamental principles of traffic assignment, and their implications for traffic flow and network efficiency. Section 3 describes the methodological approach of the study, relying on the theoretical framework of graph theory and traffic assignment principles. Section 4 presents and discusses the results, distinguishing them into graph theoretic and transportation design thematic axes, and introduces synthesized network efficiency indicators, comparing different scenarios of road infrastructure improvements. Finally, Section 5 summarizes the key findings, formulates conclusions, proposes avenues for future research.

## **Theoretical background**

### **Topological analysis of transport networks**

According to Park and Yilmaz (2010), the topology of a road network differs significantly from other common types of networks due to its “planar” design, which conforms to the Euclidean space. In planar networks, the edges (links) of the nodes do not intersect with each other (Barthelemy, 2011; Ducruet and Lugo, 2013). The representation of an urban network heavily relies on the topology of its road arteries, which in turn reflects the way a city is connected (Lin and Ban, 2013; Marshall et al., 2018). Two main representations of road networks have emerged so far. The first, and most common, representation considers path segments as edges/ links and their intersections or endpoints as nodes (Crucitti et al., 2006). Due to its simplicity, this representation has been widely adopted by numerous researchers and scientists in various traffic analyses requiring network simulations. The second representation gained attention from several researchers a few years later as they sought to interpret the

hierarchical structure of road arteries within urban areas (Barthelemy, 2011; Marshall et al., 2018). This approach assigns significance to nodes based on their connectivity with neighboring nodes, thus determining their hierarchical ranking within the network. By employing this method, the network is reshaped into a new topological representation, enabling the computation of a variety of graph theory measures. **Table 1** provides an overview of the main graph theory measures.

**Table 1. Overview of major global graph theoretic measures**

Measure	Type	Description	Formulation
Diameter	Network measure	The maximum eccentricity of the shortest path $p(i, j)$ between any two edges within the graph.	$d(G) = \max\{p(i, j) \mid i, j \in V\}$
Graph density	Network measure	The ratio of the number of edges presents in a graph to the maximum possible number of edges that the graph can have.	$d = \frac{2m}{n(n-1)}$ where $nn$ number of nodes and $mm$ number of edges
Average path length	Network measure	The mean number of steps along the shortest paths for all possible pair of nodes.	$a = \sum_{\substack{k=0 \\ s,t \in V}} \frac{d(s, t)}{n(n-1)}$ where $d(s, t)$ the shortest path from $ss$ to $tt$ and $nn$ the number of nodes.
Modularity	Network measure	How well a network can be divided into separate modules or clusters.	$M = \frac{1}{2m} \sum_{ij} \left( A_{ij} - \gamma \frac{k_i k_j}{2m} \right) \delta(c_i c_j)$ where $m$ number of edges, $A$ the adjacency matrix of $g$ , $k_i k_i$ is the (weighted) degree of $ii$ , $\gamma$ is the resolution parameter, and $\delta(c_i c_j)$ is 1 if $ii$ and $jj$ are in the same community else 0.
Efficiency	Network measure	How easily a pair of nodes can communicate and is calculated as the inverse of the shortest path between them.	$E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}}$ where $nn$ is the number of nodes and $d_{ij}$ is the shortest path between these nodes.
Degree	Centrality measure	The level of connectivity of a node within a network. It corresponds to the number of edges directly connected to a given node.	$d_c = \frac{d_i(g)}{(n-1)}$ where $d_i$ is the degree of node $ii$ , i.e., the total number of edges connected to node $ii$ in network $gg$ , and $nn$ the number of nodes in network $gg$ .
Betweenness	Centrality measure	Extent to which a node lies on the shortest paths between other pair of nodes in a network.	$b = \sum_{s,t \in V} \frac{\sigma(s, t u)}{\sigma(s, t)}$ where $\sigma(s, t)$ is the set of shortest paths in the graph and $\sigma(s, t u)$ is the number of shortest paths passing through the given node $uu$ .

Measure	Type	Description	Formulation
Closeness	Centrality measure	The ease of traversing from one node to another within a network.	$C_c = \frac{n-1}{\sum_{u=0}^{n-1} d(v,u)}$ where $d(v,u)$ is the length of the shortest path between two nodes $v$ and $u$ .
Eigenvector	Centrality measure	The transitive influence of nodes. Having more influential neighbors makes the node more important.	$Ae = \lambda e$ where $A$ is the adjacency matrix of the network multiplied by $\lambda$ .
Clustering coefficient	Centrality measure	How connected each node's neighbors are in a network.	$C_u = \frac{2T(u)}{deg(u)(deg(u)-1)}$ where $T(u)$ is the number of triangles of node $u$ and $deg(u)$ is the degree of that node.

Source: Newman (2010); Barthelemy, (2011); Tsiotas (2021); Tsiotas and Tselios (2022)

The graph theoretic measures outlined in Table 1 offer valuable insights into the structural characteristics of a road network in its total (thus they are considered as global measures). Network diameter provides information about the size of the network (Newman, 2010), while density reflects the extent of interconnectivity among nodes (Newman, 2010; Barthelemy, 2011). In addition, average path length reveals how efficiently traffic and passenger movement are transmitted between nodes (Barthelemy, 2011). Modularity is crucial in transportation networks for identifying regions or transportation hubs, illustrating how effectively the network separates into distinct clusters (Blondel et al., 2008; Fortunato, 2010). Finally, centrality measures such as degree, betweenness, closeness, eigenvector centrality, and clustering coefficient each provide insights into the importance of the nodes, indicating for instance their influence on traffic flow and accessibility (Hellervik et al., 2019).

### Transport planning framework

One of the fundamental aspects of urban transportation planning revolves around the process of predicting traffic flow on the roads (Maerivoet and De Moor, 2005). This involves the use of traffic forecasting models to anticipate future traffic patterns on road networks and form the basis for determining the need for new road infrastructure, as well as changes in land use policies (Ahmed, 2012). The history of demand modelling for person travel has been dominated by the approach that has come to be referred to as the four-step model, namely, trip generation, trip distribution, modal split, and assignment, addressing fundamental questions about travel patterns, destinations, modes, and routes (McNally, 2007). The trip generation depends on the desire for travel and its feasibility, influenced by socio-economic factors and land use characteristics such as the location and accessibility of the traffic zone, household income, or even car ownership status (Yao et al., 2008). Trip distribution involves allocating the number of movements generated and attracted to specific traffic zones. This step typically entails creating an origin-destination matrix, assigning the number of generated movements from each origin to each destination (Evans, 1970). Modal split entails distributing the trips among different modes of transport based on factors such as travel cost, comfort, and trip duration, reflecting the behavior of each person (Cingel, 2019). Finally, traffic assignment targets finding the optimal route, typically the shortest path, to accurately estimate how traffic flow will be distributed across the network (Galib et al., 2014).

## Fundamental principles of traffic assignment

Traffic assignment is based on certain principles that reflect the way drivers choose a route, considering various factors such as the congestion on the roads and knowledge of the prevailing conditions (De dios Ortúzar and Willumsen, 2024; Bell and Iida, 1997). Moreover, these principles capture the behavior of drivers, which may be either selfish or oriented toward the common welfare of all drivers. Depending on the principle applied, traffic assignment can be classified into two types. The first one allows for selecting one single-route for each OD pair, while the other allows the selection of multiple routes per OD pair (Szeto and Wong, 2012). Estimating travel time for road segments is one of the most crucial factors in traffic assignment models. In its simplest case, travel time is calculated as the time required for a user to cross the respective road segment under free-flow conditions, even though this technique fails to account the real-world representation, especially in urban areas where congestion is variable (Boyles et al., 2020). The first principle of traffic assignment, known as “all or nothing”, is grounded in this technique, where the assignment results from the estimated travel times under free-flow conditions (Saw et al., 2015). According to “user equilibrium”, which is the second are characterized by a selfish behavioral model, seeking to minimize their personal travel time without regard for its impact on other drivers within the network (Morandi, 2024). Consequently, each user selects the route that optimizes their own travel time, irrespective of the choices made by others. On the other hand, the third principle, referred to as the “system optimum”, suggests that drivers should collaborate to minimize the total travel time across the entire network (Morandi, 2024). Although this principle prioritizes network efficiency and overall performance over individual preferences, it is considered unrealistic as drivers cannot continuously be aware of the destinations of other drivers (Matheu, 2011).

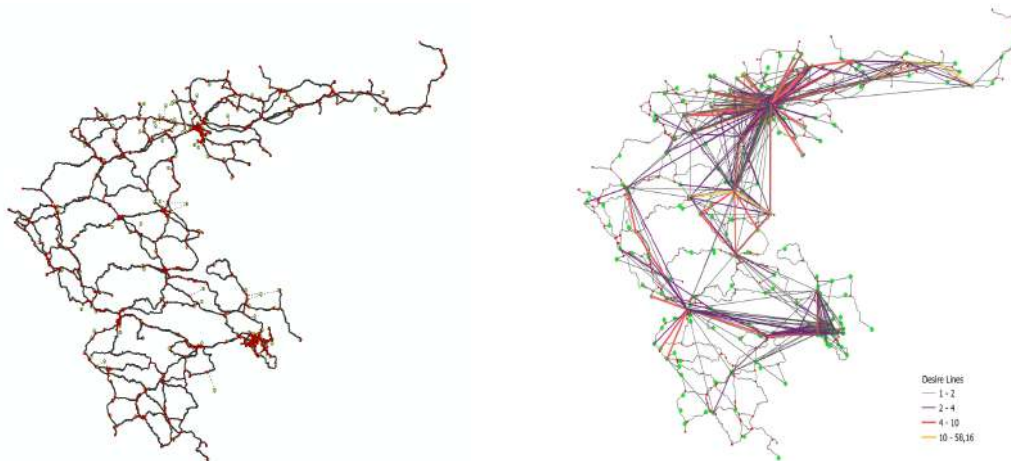
## Methodology and Data

The methodological framework of this study relies to a significant extent on the theoretical background of graph theory and the fundamental principles of traffic assignment. On this basis, complex weighted indicators are synthesized based on key metrics and results derived from the traffic assignment process. These indicators are quantified within the context of a case study focusing on the Greek national road network (Tsiotas, 2021) in a generalized form. This network is comprised of 866 nodes and 2211 links in total, where of the 866 nodes, 250 are the origin-destination zones and 616 intersections. Accordingly, the 250 links of the network are non-physical topological elements of it, as they are considered the connectors of the respective zones. The traffic zones were chosen based on two main criteria. The first criterion was the population of the zones, while the second involved ensuring coverage of the national network to the fullest extent possible. Hence, all municipalities with populations exceeding 9,500 inhabitants were selected.

The topology and the overall layout of the network were developed using the ArcGIS software package, representing the network as a directed graph utilizing two main tools. The initial tool utilized was the NetworkX library (Igual and Seguí, 2024). Network Analysis. In *Introduction to Data Science: A Python Approach to Concepts, Techniques and Applications* (pp. 151-174). Cham: Springer International Publishing.), offering comprehensive capabilities for computing graph theory measures within the Python programming language. The second tool employed was the AequilibraE library (Camargo, 2023), which was utilized for addressing traffic assignment problems within the Python programming language as well. Moreover, this library facilitated the computation of both the shortest paths between traffic zones and the generalized travel cost matrix. Afterwards, all the results were visualized within the QGIS environment.

Subsequently, a crucial prerequisite for executing the traffic assignment algorithm involved the allocation of demand for each traffic zone. This was accomplished through the application of the gravity model (Tsekeris and Stathopoulos, 2006; Tsiotas et al., 2021; Tasopoulou et al., 2023), considering both the population size of each zone and the distances between them. As a subsequent step, statistical tools were employed to analyze the results. **Figure 1 (a)** represents the adopted national road network of Greece and **Figure 1 (b)** demonstrates the results obtained from the assessment of the origin-destination matrix in the “desired lines” format. It is noteworthy to mention that the average hourly demand for road traffic is 25,706 vehicles in total.

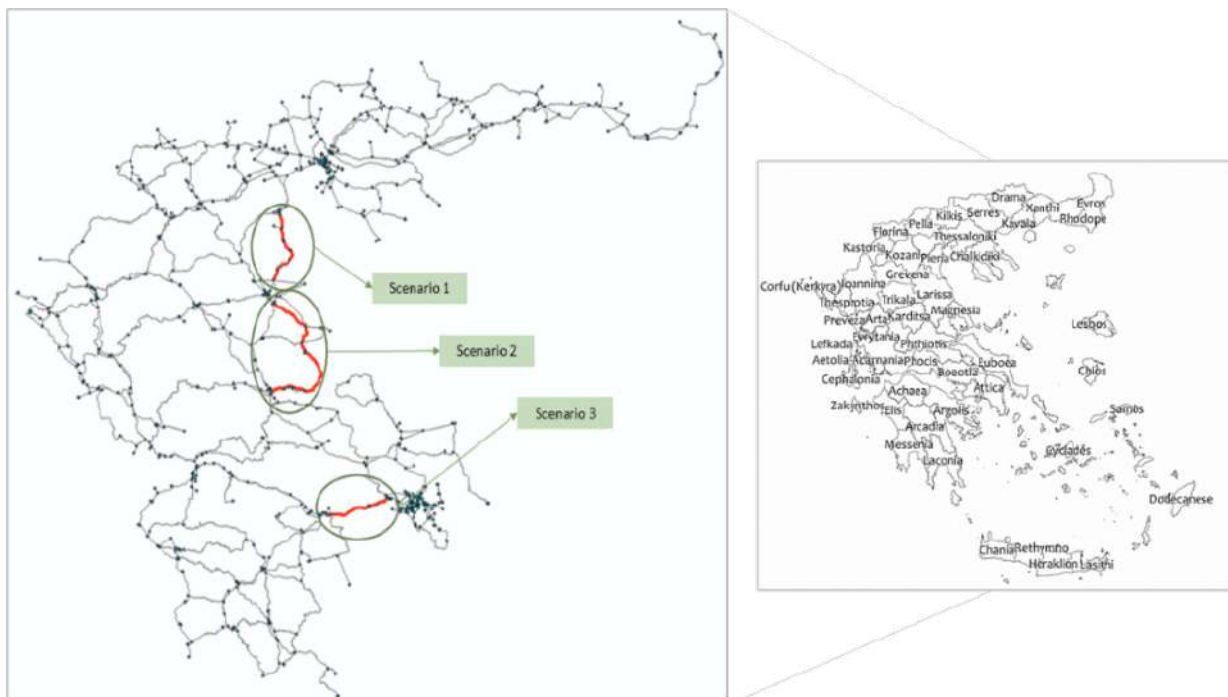
**Figure 1: (a) adopted national road network of Greece, (b) illustration of traffic flows using the “desire lines” method.**



Source: own elaboration

Furthermore, for the analysis of complex indicators that cannot be assessed independently but require comparison with values derived from network-level changes, such as the enhancement or deterioration of certain road infrastructures, three specific hypothetical scenarios were devised. These scenarios, depicted in **Figure 2**, reflect the road arteries designated for enhancement. The first scenario involves improving the Larissa-Katerini section, the second one the Lamia-Larissa, and the third one the Athens-Corinthos section. Across all scenarios, the methodology consisted of computing the unified efficiency indicator and comparing it with the same indicator calculated for the base network. This process involved iteratively running the traffic assignment algorithm to determine the generalized cost of traffic flow from each origin zone to each destination zone.

**Figure 2: (a) proposed scenarios for road infrastructure improvement, (b) the NUTS III administrative division in Greece.**



Source: own elaboration

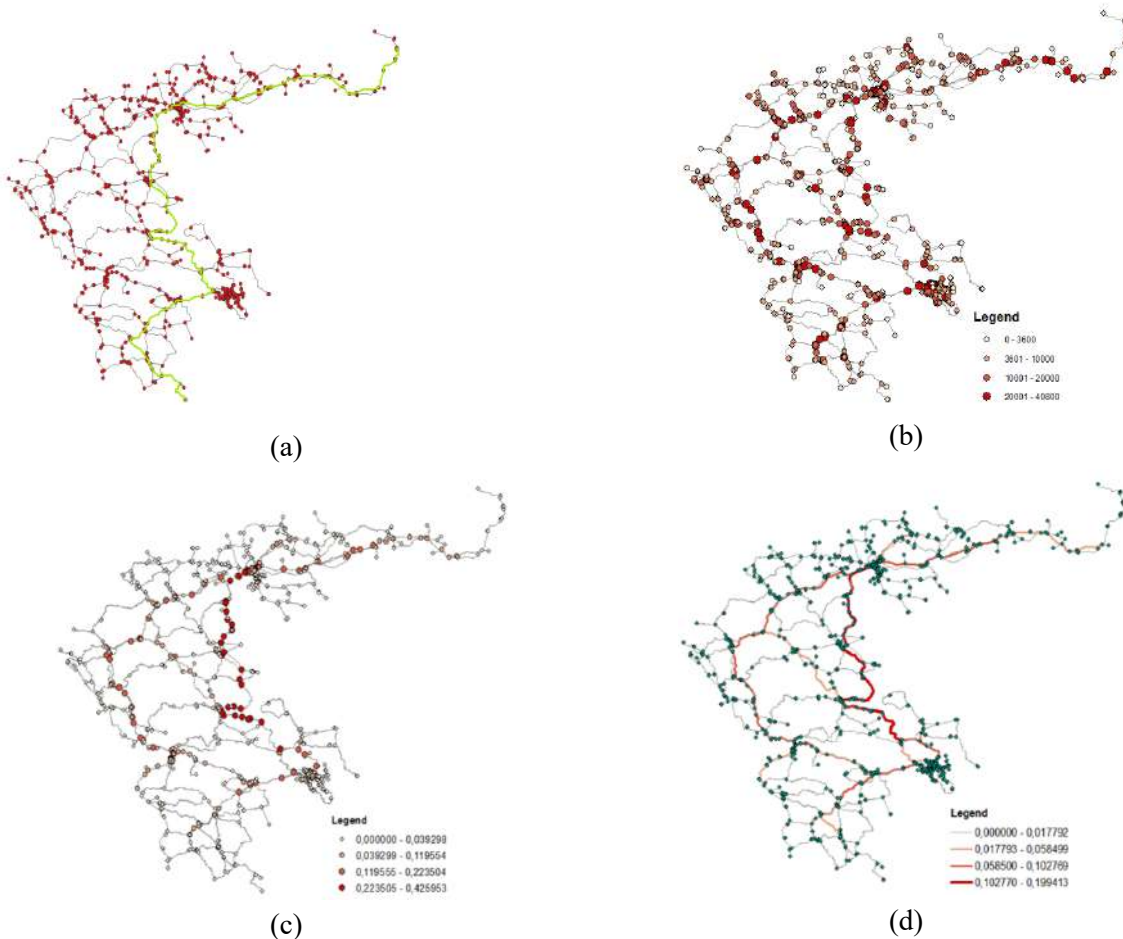
## Results and Discussion

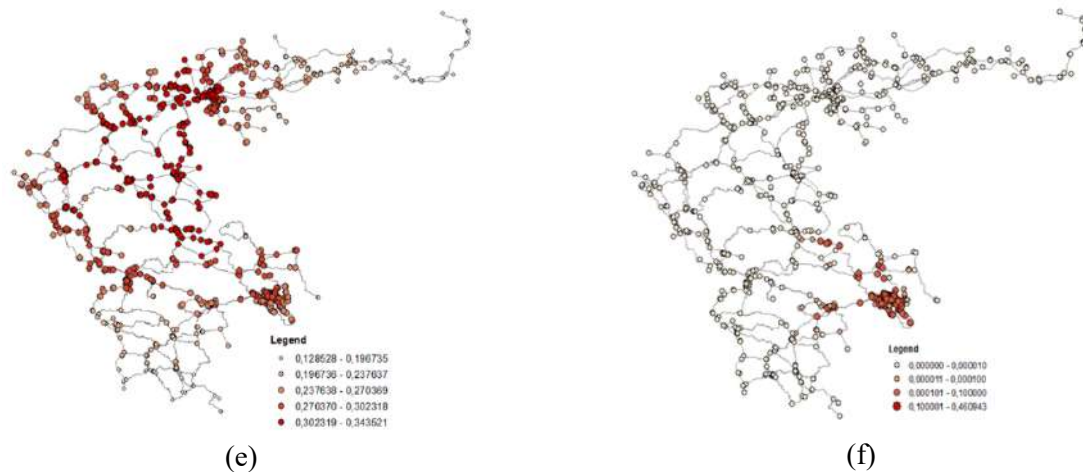
This section aims to present and explain important indicators characterizing the adopted road network. These indicators can be classified into those that derived from graph theory and those interpreting the road network from a transportation perspective. Moreover, new indicators are synthesized based on the results derived with the aim of describing the economic and operational dimensions of the road network. Finally, this section presents the results obtained through statistical analysis in an attempt to interpret the correlation that appears between specific indicators of the road network.

### Graph theory measures

In this subsection, the results of the graph theory measures corresponding to the generalized national network are presented in **Figure 3**. It is important to mention that for computing these indicators utilizing the Dijkstra algorithm (Fan and Shi, 2010) to determine the shortest paths between origin and destination nodes, we focus only on the origin-destination traffic zones of the network rather than considering all nodes.

**Figure 3: (a) diameter of the network, (b) node degree weighted by road capacity, (c) node betweenness weighted by free flow speed, (d) link betweenness weighted by free flow speed, (e) closeness centrality of network nodes weighted by free flow speed, (f) node eigenvector weighted by road capacity.**





Source: own elaboration

**Figure 3a** illustrates the diameter of the road network which signifies the longest path among the shortest routes. The diameter was determined to be 13.5 hours and derived from a matrix encompassing time distances for all pairs of zones within the network. **Figure 3b** visualizes the node degree centrality weighted by road capacity. Given the structure of the road network, it is worth pointing out that the degree is solely computed for each physical node, excluding centroids. Centroids within the network possess a singular connection, albeit non-existent in reality, distinguished by high speed and very low travel time and therefore, the degree does not serve as a representative indicator for centroids. The red-colored nodes indicate that they are connected with neighboring ones with high capacity. **Figure 3c** displays the betweenness centrality weighted by free flow speed for nodes, while **Figure 3d** does so for links of the road network. As anticipated, nodes situated along highways exhibit high betweenness centrality, since these highways serve as primary arteries connecting various regions and cities. Moreover, highways typically accommodate a substantial volume of long-distance traffic, connecting major population centers, thus reflecting their pivotal role in the road transportation network (Polyzos et al., 2014). Similarly, the links associated with highways demonstrate high betweenness centrality as well. Furthermore, betweenness centrality operates as a valuable metric for identifying critical elements, such as nodes, links, and potential bottlenecks, enabling the optimization of routing algorithms and facilitates the identification of alternative routes in case of network disruptions. **Figure 3e** presents closeness centrality of network nodes weighted by free flow speed. A node with high closeness centrality is easily and efficiently reachable from all other nodes (Tsiotas, 2021), thus serving as a crucial connecting element and facilitates the seamless movement of both people and goods throughout the transportation network. As it can be seen from the figure, the nodes exhibiting the highest closeness centrality are primarily situated in central Greece and major urban areas a result that aligns with existing literature (Polyzos, 2019, 2023; Tsiotas and Polyzos, 2024) and expectations considering that this metric relies on the computation of shortest path distances between nodes. Finally, **Figure 3f** depicts node eigenvector centrality weighted by road capacity. Nodes with high eigencentrality are those connected to other significant nodes within the network (Koschutski et al., 2005; Tsiotas, 2021). In that case, the capacity of roads acts as a weighting factor on network edges, representing that strongly connected nodes are not necessarily linked to numerous nodes but rather to those adjacent to high-capacity roads. Notably, key junctions such as those situated along Attiki Street in Athens (capital of Greece), exemplify this reflection.

### Outputs of the traffic assignment step

To distribute traffic flow across specific segments of the road network, a traffic assignment process is implemented following the principle of user equilibrium. The key requirement for executing this assignment involves establishing the traffic demand through an origin-destination matrix. To achieve this, a gravity model is employed, taking into account the population size of each zone and the distance between them, raised to a power  $\alpha$ . In line with this model, when the distance between two or more zones remains constant, areas with larger populations showcase increased mobility, thereby displaying a stronger attraction, as shown in relation (Polyzos, 2019, 2023):

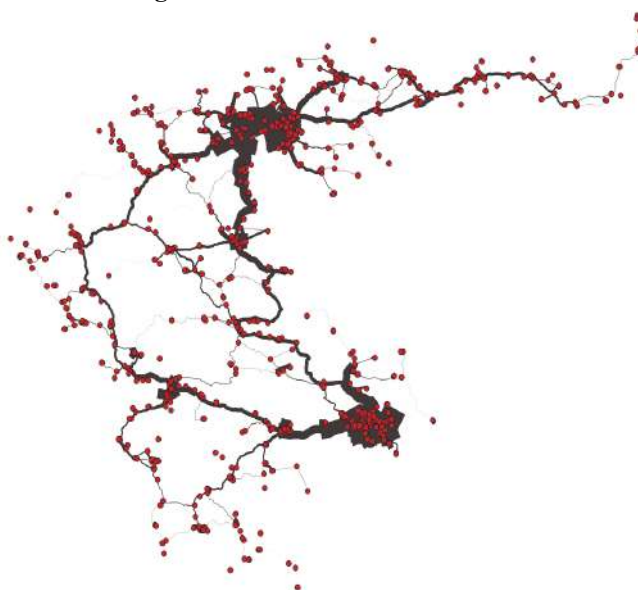


$$OD_{ij} = \frac{pop(i)pop(j)}{tt(i)^{\alpha}} \quad OD_{ij} = \frac{pop(i)pop(j)}{tt(i)^{\alpha}} \quad (1)$$

where  $pop(i)pop(j)$  denotes the product of the populations of the two zones, and  $tt(i)$  represents the minimum time distance that connects these zones.

To determine the parameter  $\alpha$ , iterative execution of the traffic assignment was necessary until the distributed traffic flows at the links of the network, converged to approximate real values. To evaluate the values, data sourced from the National Access Point of Greece (Mylonas et. al., 2023). All you need is data: the added value of National Access Points as backbone European ITS data exchange infrastructures. arXiv preprint arXiv:2310.14054.) concerning real-time dynamic traffic flows at the Toll Stations of Hellastron’s network, covering all highways of the country, was utilized. **Figure 4** presents the distributed traffic flow results, showcasing a strong correlation between the distributed traffic flow and the highways within the road network.

**Figure 4: Estimated traffic flows**



Source: own elaboration

### Synthesized indicators

This section focuses on the calculation of unified network efficiency indicator weighted by the traffic flow through different scenarios. This indicator offers insights into the performance of the network by considering traffic demand and its impact on generalized travel costs (Rodrigue et al., 2013). As outlined in the methodology, the unified efficiency metric requires comparison across different stages to gauge its effectiveness. To facilitate this comparison, three scenarios were developed as shown in **Figure 2**, each evaluating the unified efficiency indicator before and after improvements to three specific network segments. To calculate unified efficiency, the traffic assignment model was iteratively executed in all scenarios to determine the generalized travel cost from each origin zone to each destination zone. In total, the unified efficiency was calculated four times as depicted in **Table 2**.

**Table 2. Unified efficiency indicator results across all scenarios**

Scenarios	Unified efficiency indicator
Basic scenario	3.9786
Scenario 1	3.9794
Scenario 2	3.9796
Scenario 3	3.9885

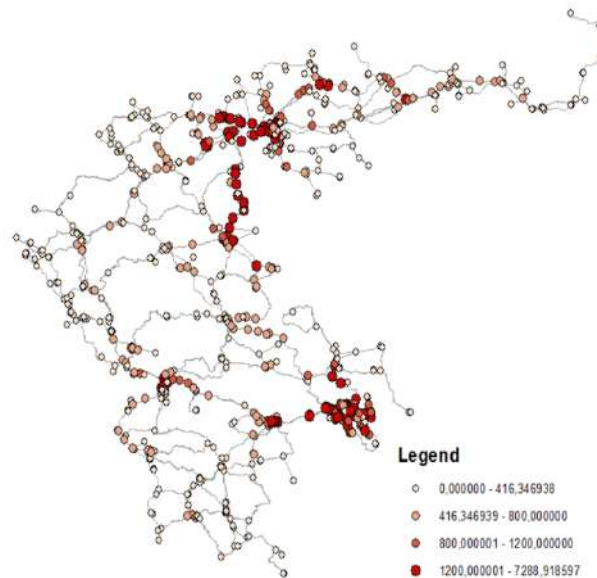
Source: own elaboration

Observing the results, it becomes evident that the efficiency of the network improves across all scenarios. Notably, the most optimal scenario is the third one, exhibiting a value of 3.9885, signifying a substantial enhancement in terms of generalized travel cost. Therefore, based on these findings, Scenario

3 emerged as the most optimal choice for prioritizing improvements, suggesting that investing in enhancements along the Larissa-Katerini road would result in the most substantial benefits for overall network efficiency and performance.

The next synthesized indicator that is presented in **Figure 5**, is the node degree weighted by traffic flow as derived from the outcomes of the traffic assignment process.

**Figure 5: Node degree weighted by estimated traffic flows**



Source: own elaboration

As it can be seen from the above figure, the nodes exhibiting high degree are primarily concentrated in the two major urban centers of Greece, Nevertheless, several nodes exhibiting high degrees are also situated along highways, particularly along the route linking these urban centers. These findings can be considered logical according to the S-type model of spatial development in Greece (Tsiotas and Polyzos, 2023), given that the most important traffic flows resulting from the traffic assignment are also concentrated in these areas, as illustrated in **Figure 4**.

However, it is noteworthy to compare **Figure 3b** with **Figure 5**. In the former, node degree is computed by considering road capacity as the weighting factor for links, whereas in the latter by considering estimated traffic flows. In **Figure 3b**, the capacity reflects the presence of highways across the country. Consequently, given the extensive coverage of highways throughout the network, it is unsurprising to find high-degree nodes distributed across the entire network. On the other hand, in the second figure, estimated traffic flow acts as a “correction factor” for node degree centrality, reallocating strategically important nodes based on traffic demand. For that reason, we observed that nodes with high degrees are primarily located in regions with traffic demand, differing from the picture identified in the first case.

### Statistical and quantitative assessments

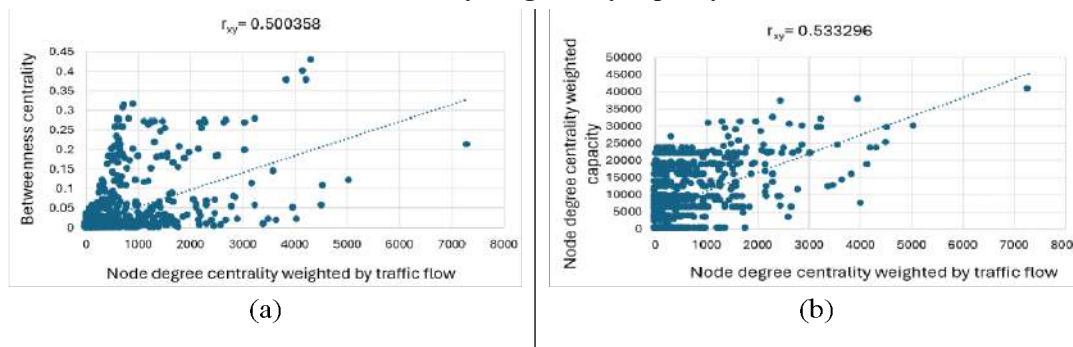
The objective of this subsection is to assess the extent to which the proposed indicators provide a good picture on the operation of the road network, the way that people are moved from one region to another, and on the identification of key network components that best represent these aspects. In that evaluation, the indicators are treated as continuous variables, and thus their correlation is quantified using the Pearson correlation (Cohen et al., 2009; Walpole et al., 2012):

$$r_{xy} = \frac{Cov(\mathbf{x}, \mathbf{y})}{\sqrt{Var(\mathbf{x})} \cdot \sqrt{Var(\mathbf{y})}} = \frac{Cov(\mathbf{x}, \mathbf{y})}{\sigma_x \cdot \sigma_y} \quad (2)$$

where  $Cov(x,y)$  is the covariance of  $x,y$ , and  $Var(x)=\sigma_x$ ,  $Var(y)=\sigma_y$  are the variances of the vector variables respectively. This evaluation involves two primary aspects: a) analyzing how node betweenness centrality relates to node degree centrality when edge weighting is based on traffic flow, and b) exploring the relationship between node degree centralities when edge weighting factors are on the one hand estimated traffic flows and on the other capacity of the roads.

As regards the first comparison, the underlying assumption is that these metrics are interrelated. Betweenness centrality identifies nodes frequently encountered on the shortest paths within the network, while degree centrality weighted by traffic flow highlights nodes through which a significant part of traffic passes (Koschutski et al., 2005; Barthelemy, 2011). Therefore, given that travelers typically opt for routes minimizing travel time, there is an anticipated correlation between these two metrics. The second assessment seeks to compare the operational and economic dimensions of the network, premised on two key assumptions. Firstly, as already mentioned, degree centrality weighted by traffic flow identifies nodes through which a significant part of traffic flows. Secondly, degree centrality weighted by capacity highlights nodes adjacent to high-traffic-capacity road infrastructures. Consequently, comparing these two measures offers insights into the extent to which the network effectively serves the daily transportation needs of society. **Figure 6** presents the results derived from the aforementioned two assessments.

**Figure 6: (a) Scatterplot between node degree centrality and betweenness centrality weighted by traffic flow and (b) scatterplot between node degree centrality weighted by traffic flow and node degree centrality weighted by capacity**



Source: own elaboration

As can be seen from **Figure 6a** the degree to which the two measures are correlated is approximately equal to 0.50. This value indicates that the two measures show a positive and moderate correlation between them. Therefore, betweenness centrality can be considered to be a satisfactory estimator of traffic flows particularly in situations where comprehensive data and tools for traffic analyses are unavailable. **Figure 6b** presents the correlation between the two measures, showing a correlation of around 0.53. This indicates that while the road network design adequately meets the needs of travelers, there may be further room for optimization from an economic perspective.

## **Conclusions**

The objective of this paper was to comprehend the functional and economic dimensions of road transportation networks. Hence, a literature review was conducted focusing on graph theory and on the identification of measures that can support the analysis of road network topology and the centrality of its individual components. In addition, the fundamental principles of traffic assignment models in a transport network were presented. Based on this foundation, a case study of the national road network of mainland Greece was constructed to test associated metrics and methodologies, yielding valuable insights about their utility. Key findings from the case study include: i) the diameter of the analysed road network is significantly influenced by the geomorphology of mainland Greece, ii) nodes with high degree centrality weighted by the traffic capacity of network edges are primarily located along national highways, iii) both nodes and edges with high betweenness centrality are found along national highways due to their high speeds iv) nodes with high closeness centrality are located either in central regions of mainland Greece or near major urban centers, v) strongly connected nodes are not necessarily joined

with many other nodes, but with nodes adjacent to high-capacity roads, vi) major “poles” of intercity travel generation and attraction are found in urban areas corresponding to Athens, Thessaloniki, Patras, and Larissa, due to their significant population densities, economic activities, and strategic locations within the national transportation network, vii) road infrastructures with the highest traffic flow for intercity travel are highways, viii) the unified network efficiency indicator is a useful tool for evaluating investments in road infrastructures aimed at simultaneously enhancing the functional and economic performance of a road network, ix) betweenness centrality can be considered a satisfactory estimator of traffic flows in cases where sufficient data and tools for traffic analysis are unavailable, x) the design of the road network adequately, though not optimally, meets the needs of travellers.

Proposals for extending the current research can follow several pathways. Firstly, it is recommended to recalculate and analyse all previously used indicators utilizing a more accurate network that incorporates a greater number of secondary road arteries to obtain more precise and comprehensive insights into the network’s performance and to better capture the complexity of real-world traffic flows. Secondly, additional indicators should be examined, and their distribution at the network level should be investigated to determine in greater detail scale-free properties and power-law conditions. Finally, a sensitivity analysis can be conducted with different input data concerning travel demand to evaluate the robustness of the model and understand how variations in travel patterns impact network performance.

## **References**

- Abeyrathne, R. B. A. H., and G. Lanel. “A Study on Graph Theory Properties in Human Blood Circulatory System”. *International Journal of Scientific Research Publications* 11 (2021): 444.
- Ahmed, Bayes. “The Traditional Four Steps Transportation Modeling Using a Simplified Transport Network: A Case Study of Dhaka City, Bangladesh”. *International Journal of Advanced Scientific Engineering and Technological Research* 1, no. 1 (2012): 19-40.
- Anderson, T., and S. Dragičević. “Complex Spatial Networks: Theory and Geospatial Applications”. *Geography Compass* 14, no. 9 (2020): e12502.
- Banister, D., K. Anderton, D. Bonilla, M. Givoni, and T. Schwanen. “Transportation and the Environment”. *Annual Review of Environment and Resources* 36 (2011): 247-270.
- Barabasi, A.-L. “Network Science”. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 371, no. 1987 (2013): 20120375
- Barthelemy, M. “Spatial Networks”. *Physics Reports* 499 (2011): 1–101.
- Boyles, S. D., N. E. Lowmes, and A. Unnikrishnan. *Transportation Network Analysis: First Public Beta Version*. 2020.
- Camargo, P. “AequilibraE and Tradesman: Current State of Affairs of Modelling with Open-Source Software”. In *Australasian Transport Research Forum (ATRF), 44th, 2023, Perth, Western Australia, Australia*. 2023.
- Capello, R. *Regional Economics*. New York: Routledge, 2016.
- Cingel, M., J. Čelko, and M. Drličiak. “Analysis in Modal Split”. *Transportation Research Procedia* 40 (2019): 178-185.
- Cohen, I., Y. Huang, J. Chen, J. Benesty, and J. Chen. “Pearson Correlation Coefficient”. In *Noise Reduction in Speech Processing*, 1–4. 2009.
- Crucitti, P., V. Latora, and S. Porta. “Centrality Measures in Spatial Networks of Urban Streets”. *Physical Review E* 73, no. 3 (2006): 036125.
- Ducruet, C., and I. Lugo. “Structure and Dynamics of Transportation Networks: Models, Methods and Applications”. In *The SAGE Handbook of Transport Studies*, 347–64. 2013.
- Evans, A. W. “Some Properties of Trip Distribution Methods”. *Transportation Research* 4, no. 1 (1970): 19-36.
- Feng, C. M., and C. H. Hsieh. “Resource Allocation for Sustainable Urban Transit from a Transport Diversity Perspective”. *Sustainability* 1, no. 4 (2009): 960-77.
- Fortunato, S. “Community Detection in Graphs”. *Physics Reports* 486 (2010): 75–174.
- Galib, S. M. *Applying Minority Game to Road Traffic Assignment*. PhD diss., Swinburne University of Technology, 2014.
- Hellervik, A., L. Nilsson, and C. Andersson. “Preferential Centrality: A New Measure Unifying Urban Activity, Attraction and Accessibility”. *Environment and Planning B: Urban Analytics and City Science* 46, no. 7 (2019): 1331–46.
- Hesse, M., and J. P. Rodrigue. “The Transport Geography of Logistics and Freight Distribution”. *Journal of Transport Geography* 12, no. 3 (2004): 171–84.
- Igual, L., and S. Seguí. “Network Analysis”. In *Introduction to Data Science: A Python Approach to Concepts, Techniques and Applications*, 151-74. Cham: Springer International Publishing, 2024.
- Kondo, R., Y. Shiomi, and N. Uno. “Network Evaluation Based on Connectivity Reliability and Accessibility”. In

- Network Reliability in Practice: Selected Papers from the Fourth International Symposium on Transportation Network Reliability, 131–49. New York, NY: Springer, 2011.
- Koschutzki, D., K. Lehmann, L. Peeters, and S. Richter. “Centrality Indices”. In *Network Analysis*, edited by U. Brandes and T. Erlebach, 16-61. Berlin: Springer-Verlag, 2005.
- Ladias C.A., Ruxho F., Teixeira F., Pescada S., 2023, “The regional economic indicators and economic development of Kosovo”, *Regional Science Inquiry*, Vol. XV, (1), pp. 73-83
- Lin, J., and Y. Ban. “Complex Network Topology of Transportation Systems”. *Transport Reviews* 33, no. 6 (2013): 658-85.
- Liu, G., P. Gao, and Y. Li. “Transport Capacity Limit of Urban Street Networks”. *Transactions in GIS* 21, no. 3 (2017): 575-90.
- Marshall, S., J. Gil, K. Kropf, M. Tomko, and L. Figueiredo. “Street Network Studies: From Networks to Models and Their Representations”. *Networks and Spatial Economics* 18, no. 3 (2018): 735-49.
- McNally, M. G. “The Four-Step Model”. In *Handbook of Transport Modelling*, vol. 1, 35-53. Emerald Group Publishing Limited, 2007.
- Morandi, V. “Bridging the User Equilibrium and the System Optimum in Static Traffic Assignment: A Review”. *4OR* 22, no. 1 (2024): 89–119.
- Newman, M. E. J. *Networks: An Introduction*. Oxford: Oxford University Press, 2010.
- Nijkamp, P., A. Reggiani, and W. F. Tsang. “Comparative Modelling of Interregional Transport Flows: Applications to Multimodal European Freight Transport”. *European Journal of Operational Research* 155, no. 3 (2004): 584-602.
- Polyzos, S. *Regional Development*. 2nd ed. Athens: Kritiki Publications, 2019. (In Greek).
- Polyzos, S., D. Tsiotas. “Interregional Transport Infrastructures and Regional Development: A Methodological Approach”. *Theoretical and Empirical Researches in Urban Management* 18, no. 2 (2023): 5-31.
- Polyzos, S., D. Tsiotas. “The Contribution of Transport Infrastructures to the Economic and Regional Development: A Review of the Conceptual Framework”. *Theoretical and Empirical Researches in Urban Management* 15, no. 1 (2020): 5-23.
- Polyzos, S., D. *Urban Development*. 2nd ed. Athens: Kritiki Publications, 2023. (In Greek).
- Roth, A., and T. Kåberger. “Making Transport Systems Sustainable”. *Journal of Cleaner Production* 10, no. 4 (2002): 361–71.
- Ruxho F., Ladias C.A, 2022 “Increasing funding for the regional industry of Kosovo and impact on economic growth” *Regional Science Inquiry Journal*, Vol. XIV. (1), pp. 117-126
- Ruxho F., Ladias C.A, Tafarshiku A., Abazi E., 2023 “Regional employee’s perceptions on decent work and economic growth: labour market of Albania and Kosovo”, *Regional Science Inquiry*, Vol. XV, (2), pp.13-23.
- Ruxho F., Ladias C.A., 2022 “The logistic drivers as a powerful performance indicator in the development of regional companies of Kosovo” *Regional Science Inquiry Journal*, Vol. XIV. (2), pp. 95-106
- Ruxho F., Petropoulos D., Negoro D.A. 2024. “Public debt as a determinant of the economic growth in Kosovo”, *Sustainable Regional Development Scientific Journal*, Vol. I, (1), pp. 55-67
- Saw, K., B. K. Katti, and G. Joshi. “Literature Review of Traffic Assignment: Static and Dynamic”. *International Journal of Transportation Engineering* 2, no. 4 (2015): 339-47.
- Szeto, W. Y., and S. C. Wong. “Dynamic Traffic Assignment: Model Classifications and Recent Advances in Travel Choice Principles”. *Central European Journal of Engineering* 2 (2012): 1-18.
- Tasopoulou, T., D. Tsiotas, and S. Polyzos. “Investigating the Interaction Between the Topology of Bus Transport Networks and Regional Development in Greece”. *Regional Science Inquiry* 15, no. 2 (2023): 25–46.
- Tsekeris, T., and A. Stathopoulos. “Gravity Models for Dynamic Transport Planning: Development and Implementation in Urban Networks”. *Journal of Transport Geography* 14, no. 2 (2006): 152-60.
- Tsiotas, D. “Drawing Indicators of Economic Performance from Network Topology: The Case of the Interregional Road Transportation in Greece”. *Research in Transportation Economics* 90 (2021): 101004.
- Tsiotas, D., and S. Polyzos. “Transportation Networks and Regional Development: The Conceptual and Empirical Framework in Greece”. *Sustainable Regional Development Scientific Journal* 1, no. 1 (2024): 15–39.
- Tsiotas, D., and V. Tselios. “Decomposing the Complexity of Interregional Commuting: A Multilayer Network Approach”. *Networks and Spatial Economics*, 2022. <https://doi.org/10.1007/s11067-022-09578-5>.
- Tsiotas, D., Krabokoukis, T., & Polyzos, S. 2020. Detecting interregional patterns in tourism seasonality of Greece: A principal components analysis approach. *Regional Science Inquiry*, 12(2), 91-112.
- Tsiotas, D., N. Axelis, and S. Polyzos. “A Methodological Framework for Defining City Dipoles in Urban Systems Based on a Functional Attribute”. *Cities* 119 (2021): 103387.
- Walpole, R. E., R. H. Myers, S. L. Myers, and K. Ye. *Probability & Statistics for Engineers & Scientists*. 9th ed. New York: Prentice Hall, 2012.
- Yao, L., H. Guan, and H. Yan. “Trip Generation Model Based on Destination Attractiveness”. *Tsinghua Science and Technology* 13, no. 5 (2008): 632-35.