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Location of Road Freight Transportation Logistics Hubs in Iran: A Network Analysis Approach

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ABSTRACT

Objective: The aim of this study is to identify optimal hubs in Iran's road freight transport network using a network-analysis approach. The research seeks to reveal the actual structure of the country's freight flows and provide a clustered network pattern by addressing the limitations of traditional hub-location methods, which often ignore both direct and indirect interactions among nodes.

Methods: For the network analysis, freight-flow data among the 31 provinces of Iran for the year 2023 were extracted, and a weighted matrix was constructed based on each province's share of total outbound cargo. A threshold was then applied to remove low-importance links, and using computational network metrics in Gephi, the network structure, clusters, and selected hubs within each cluster were identified.

Results: The results indicate that Iran's road transport network consists of four main clusters, each with a distinct freight-flow pattern. Analysis of centrality measures and clustering coefficients showed that Tehran, Hormozgan, Khuzestan, and Khorasan Razavi act as key network hubs, ranking highly in terms of flow intensity, brokerage roles, and network influence.

Conclusion: The findings demonstrate that network analysis provides a structural, flow-based framework for hub location and can compensate for the shortcomings of classical models and expert-judgment-based approaches. Since the identified hubs are located across different geographic clusters, implementing this structure could reduce transportation costs, enhance efficiency, and support logistics development policies.

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1. Introduction

Logistic hubs, as an important infrastructure within transportation systems in many countries, are designed to reduce logistics costs through using mathematical and planning knowledge. The way that makes this issue possible is that we must reduce direct/indirect connections between origins and destinations of goods. To achieve these goals, there is a vital need to have some centers to handle the collection, sorting, and distribution of goods, and these strategic centers are called logistic hubs (Campbell & O'Kelly, 2012).

Since this idea has a significant impact on the efficiency of transportation systems and goods flow, The World Bank's periodic reports on the Logistics Performance Index illustrate that countries with stronger logistics can achieve higher GDP and trade growth by 1% and 2%, respectively. Thus, logistic hubs can play a vital role through their strategic placement. In addition to the issue of supply chain costs reduction through economies of scale, reducing transportation, warehousing, and handling expenses, especially amid population connectivity, the aims of environmental planning also can be achieved.

Logistic hubs can provide timely delivery by reasonable planning of material flows, influencing decision-making of all players in the supply chain through integration of transportation, warehousing, freight consolidation, and distribution systems. Such hubs consolidate all facilities in a dispersed logistics network to coordinate cargo planning and provide value-added services, like packaging.

Logistics can be considered as a big network, and in this network, we can consider provinces as the nodes. In non-hub networks, these unplanned node connections lead to inefficient low-capacity vehicle use. In fact, economies of scale are almost impossible. Hub consolidation reduces costs, empowers efficiency, and, as a other valuable result, can lower harmful environmental impacts (e.g., CO2 emissions). In this network, Supply chain success, network planning, and distribution system could be affected by numerous factors, and hub location selection is one of the most important factors (Gao & Dong, 2013; Lium, Crainic & Wallace, 2009).

There are two main methods: multi-criteria decision making (expert-based) and mathematical programming (e.g., heuristic/stochastic), but both of them are deficient in one aspect; they neglect nodes' interrelationships (Vieira & Luna, 2016); however, a network approach is capable of addressing this by analyzing provincial connections.

The study of transportation networks traces its origins to early analyses of water-based systems, notably Pitts' examination of Russian river networks, and this has been expanded by geographers in the 1960s-1970s. They discovered the relationship between road/rail infrastructure and economic growth. Among these scientists, Karel Kansky was eminent as a pivotal figure due to his seminal study in the field of network topology, that even now it remains a key reference (Newman, 2010) . O'Kelly (1986, 1992) had a significant impact on theoretical advancements in the field of hub network modeling due to his introduction of the first mathematical framework for optimizing hub locations. Subsequent research has diversified with the aim of addressing applications in transportation and communications, though Campbell and O'Kelly (2012) believe that these models remain underrepresented compared to telecommunication-focused studies.

In recent years, Iran's logistics infrastructure has faced significant challenges, including the dispersion of cargo centers, weak integration among terminals, the absence of clustered transportation networks, and inefficiencies in interprovincial flows. This situation is reflected in official reports such as the Logistics Performance Index (LPI), which ranks Iran below the regional and global averages (World Bank, 2023). The road transport sector, responsible for over 90% of domestic freight movement, lacks a systematic framework for establishing efficient hubs, and location decisions are often made based on sectoral considerations rather than network analysis(Zabihi & Gharakhani, 2018).

Consequently, the network has developed heterogeneously, resulting in high logistics costs and an inability to leverage economies of scale.

Given the development of regional transit projects such as the North–South Corridor, the Silk Road, and the East–West Corridor, as well as the country's need to enhance the competitiveness of non-oil exports, the establishment of logistics hubs based on the actual structure of freight flows has become a strategic necessity. Since the failure of previous logistics center projects was largely due to the lack of a network-oriented perspective and the neglect of indirect relationships, the network-analysis approach employed in this study addresses a practical, rather than purely academic, need. It can accurately identify bottlenecks, influential nodes, and the cluster structure of cargo exchanges, providing an evidence-based foundation for decision-making by policymakers. The aim of this study is to evaluate Iran's road freight network using graph analysis to identify central nodes as potential hubs. Gephi (0.10) software is considered to do this graph mining.

The subsequent sections of the article are organized as follows: Section 2 provides a comprehensive review of the literature and related studies. Section 3 presents the methodological framework of the study, including the concepts of complex networks, the network indicators and their variables, and the data-analysis procedures. After the analysis and presentation of the findings in Section 4, Section 5 offers the conclusions, outlines the study's limitations, and provides recommendations for future research.

2. Literature review

Recent studies in logistics have increasingly focused on balancing real-world constraints with computational efficiency. Espejo et al. (2023) examined a single-allocation hub location model that deliberately omitted capacity constraints, streamlining variables while challenging conventional distance-cost assumptions. Their median-based approach traded off capacity considerations for improved scalability through branch-and-bound methods.

This contrasts sharply with the study of Wu et al. (2022), who prioritized capacity limitations in their solution to an urban postal service's hub location-routing problem (HLRP). Their metaheuristic algorithms simultaneously optimized pickup-delivery operations and vehicle capacity constraints - a more realistic approach for practical applications.

The field has particularly benefited from spatial analytics innovations. Khairunissa and Lee's (2022) South Korean case study stands out, where they cleverly combined GIS data with hybrid PSO-GA algorithms. By translating spatial parameters into mathematical variables, they produced solutions that held up under empirical testing.

Researchers have also grappled with uncertainty in hub selection. Ghosar and Senar (2021) made notable progress here, blending clustering techniques with MCDM for Turkey's logistics networks. Earlier, Čupić and Teodorović (2014) had tackled Serbia's freight sector with their multi-objective model optimizing both hub numbers and vehicle allocation. Meanwhile, Lin et al. (2013) took an interesting approach by constraining locations based on walking distances while accounting for infrastructure costs.

The broader literature reveals fascinating developments. After Ishfaq and Sox (2011) demonstrated their multiple-allocation p-hub median model's effectiveness for intermodal networks, subsequent work like Zhang et al.'s (2021) hybrid MCDM approach for China's BRI projects pushed the field further. Their integration of GRA and TOPSIS particularly highlighted how connectivity metrics drive multimodal performance.

Sustainability concerns are reshaping hub location strategies. Smith's (2025) Oman case study showed how eco-friendly logistics can boost competitiveness - findings that align with Jane's (2025) work on green ports. Bai et al.

(2025) proposed an innovative urban solution: leveraging metro systems for freight distribution to reduce congestion and emissions, a concept Tehran might adapt.

Recent methodological advances are particularly exciting. Haseli et al.'s (2025) fuzzy Z-number approach handles decision uncertainty remarkably well, while Attar et al. (2024) built impressive resilience into LTL networks. Xie et al. (2025) and Baruah (2024) both emphasized intermodal connectivity, though focusing on different contexts - BRI projects and Assam's inland ports respectively. The optimization toolkit keeps expanding too. Naganawa et al.'s (2024) Physical Internet model achieved dramatic emissions cuts, while Guo et al. (2024) cleverly adapted to urban lease fluctuations. Oh et al.'s (2025) spatial analysis method HUBI-COV could significantly improve the issue of hub placement.

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Practical applications abound, from Rahman et al.'s (2025) last-mile delivery optimizations to Fabry et al.'s (2024) automotive logistics centers. Zhang et al.'s (2025) two-phase BRI hub selection method might particularly interest Iranian planners seeking global trade alignment.

The advantage of network analysis in this study over previous research is that —unlike most recent studies in the field of hub location, which predominantly rely on mathematical models, GIS-based methods, metaheuristic algorithms, or MCDM techniques—this research introduces a fully network-oriented framework. In this framework, hub location is determined not by predefined criteria but by the actual structure of freight flows, the direct and indirect relationships among provinces, and the formation of communities within the transportation network. For the first time in Iran, this study analyzes the national road transport system as an interconnected network with both direct and indirect relations, and by combining flow-weighted link assignments with an optimized threshold for inter-node connections, it applies advanced complex-network metrics—such as centrality measures, modularity, and clustering coefficient—to identify hubs that are structurally genuine, rather than merely numerically optimal. Moreover, unlike studies that determine each hub through a single optimization problem, an important contribution of this research is demonstrating that each network community has its own independent hub, and that hub selection must be based on the internal behavior of each community rather than the network as a whole. Therefore, the key contribution of this article is the development of a comprehensive, structural, and flow-based network framework for logistics hub location—a methodological gap that is evident both in the Iranian literature and in many international studies.

The methodological framework proposed in this study departs substantially from conventional applications of network analysis in the transportation and hub-location literature. First, whereas most prior studies have employed network analysis merely to describe network topology or to model flow patterns, this paper simultaneously examines the macro-level architecture of the network (i.e., community structure) and the intra-cluster dynamics within each group, integrating both layers in the hub-selection process. Second, classical hub-location models—including p-hub median formulations, single- and multiple-allocation schemes, and MCDM approaches—generally overlook indirect interactions among nodes. In contrast, the network-analytic approach adopted here incorporates the full chain of direct and indirect influences by employing centrality measures, weighting inter-node relationships based on each node’s contribution to total flows, and filtering out weak ties using empirically grounded thresholds. This directly addresses a well-noted limitation of traditional decision-making models in the literature.

3. Methodology

3.1 *Fundamental Concepts*

One of the fundamental issues in transportation systems is how to send flows (of people, goods, or information) from a source to various destinations. Generally, there are two types of flow transmission networks: Direct Delivery

Networks and Hub-and-Spoke Networks. In direct delivery networks, which are traditional flow transmission systems, the flow is sent directly from the source to the destination. These types of systems are particularly used in situations where there is a high volume of flow and a need for rapid delivery. Conversely, when there are many sources and destinations, with a low volume of flow transmitted between them and numerous common destinations, it is not cost-effective to establish a complete network. To take economic advantage efficiencies and improve service levels, hub-and-spoke networks can be utilized. A direct delivery network with n nodes in a complete directed network has $n(n-1)$ arcs (Lopes et al., 2016).

Figure 1. A complete network with 11 nodes (Mata, 2020).

As illustrated in Figure 1, the number of connections is excessively high, and transportation in such a system is certainly not cost-effective. Now, if in a network with n nodes, one of the nodes is designated as a hub and the other nodes are connected through this hub, $2(n-1)$ directed arcs will be created to establish communication between each pair of distinct source and destination nodes. Therefore, under similar conditions, the hub-and-spoke network has the capacity to serve a greater number of nodes compared to the first system (see Figure 2).

Figure 2. A network with one hub and 11 nodes (Mata, 2020).

In mathematics, the term "network" refers to a collection of elements known as vertices or nodes, which are interconnected through edges or links formed by interactions. Many significant scientific problems can be expressed and studied empirically using networks. For example, biological and social patterns, the World Wide Web, metabolic networks, food webs, neural networks, and pathological networks are just a few instances of real-world issues that can be mathematically represented and analyzed to explore certain unexpected structural characteristics. Most of these networks possess a specific social structure that is crucial for understanding the dynamics of the network (Barabási, 2016).

If a network has a specific direction for each edge, it is called a directed network; otherwise, it is referred to as an undirected network. On the other hand, a network in which the connections between nodes have varying strengths is known as a weighted network; that is, the weight of the connections between nodes is significant (Newman, 2010). For example, in a freight transportation network, while the existence of cargo exchange between two provinces is important, the strength of the connection between these two provinces is even more critical, which can be measured by the volume of cargo exchanged between them.

3.2 Network Statistics

Nodes and Edges: If we describe a network mathematically as the state of a system at a given point in time using nodes (vertices) and edges (connections), we can represent it as a graph or a matrix to clarify the relationships between the nodes and the connections. In other words, a network G is a pair G=(V,E) that consists of a set of nodes V(G) which are connected by a set of edges E(G). If we denote the number of nodes by n, the matrix formed will be an n×n adjacency matrix $A=(a_{ij})$, where each entry a_{ij} indicates the presence or absence of a connection between nodes i and j in this matrix, such that:

$$a_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ are adjacent} \\ 0, & \text{otherwise.} \end{cases}$$

This means that in the adjacency matrix, if there is a connection between nodes i and j, we will have the number one, and otherwise, we will have the number zero (Jackson, 2008).

In an undirected network, the adjacency matrix is symmetric, meaning that $a_{ij}=a_{ji}$. In contrast, in a directed network, due to the connection from one node to another, the adjacency matrix is not necessarily symmetric. The degree of a node reflects the number of connections that a node has within the network and indicates the number of logistical partners for each node. In this context, Ki represents the degree index of node i, and a_{ij} refers to the entries in the initial commercial matrix (Newman, 2010).

$$K_i = \sum_{j=1}^{n} a_{ij} \tag{1}$$

In a directed network, each node (or vertex) has two degrees: in-degree and out-degree. The in-degree reflects the number of edges and connections entering a vertex, while the out-degree indicates the number of connections leaving a vertex. Given that the entries of a directed adjacency matrix are defined as $a_{ij}=1$ in the presence of a relationship between nodes i and j, the in-degree and out-degree can be expressed as follows:

$$K_i^{in} = \sum_{j=1}^{n} a_{ij} \quad , \quad K_j^{out} = \sum_{i=1}^{n} a_{ij} \tag{2}$$

Thus, the total number of edges (connections) in the network, denoted as m, is given by the following relationship:

$$m = \sum_{i=1}^{n} k_i^{in} = \sum_{j=1}^{n} k_j^{out} \tag{3}$$

Node strength: reflects the total interactions of each node within the network and is calculated within the framework of a weighted adjacency matrix as follows: S^t_i represents the strength of node i, and W^t_{ij} denotes the entries of the weighted adjacency matrix (Newman, 2010).

$$S_i^t = \sum_j W_{ij}^t \tag{4}$$

Density: This index measures the cohesiveness and connectivity of the network. It allows for the assessment of the degree of convergence, whereby a higher density index indicates that the logistics network has become more convergent, leading to an increase in the number of relationships and the volume of logistical exchanges within the network. The density index is calculated as the ratio of the total number of edges or connections to the total number of nodes in the network, as follows: where l represents the total number of edges and N denotes the total number of nodes in the network (Jackson, 2008).

$$D = \frac{2L}{N(N-1)} \tag{5}$$

Clustering Coefficient: Similar to the node strength index which focuses on the strength of the connection between nodes ii and j, this index also incorporates the strength of the connections between nodes ii and h and nodes j and h in its analyses. In other words, it examines a three-way connection within the network and assesses the degree to which a node is inclined to establish more relationships (in terms of quantity and strength) with a network of other nodes (Newman, 2010). In this context, if two provinces are selected within the road freight transport network, the probability of these two provinces having a freight transport relationship with each other can be calculated as follows. The clustering coefficient enables the assessment of the intensity of a province's inclination to form a greater number of relationships with provinces it has transport connections with. Unlike other aforementioned statistics, any province with a lower clustering coefficient holds greater significance in the network.

$$C_i^t = \frac{\frac{1}{2}\sum_{j\neq i}\sum_{h\neq(i,j)} W_{ij}^{\frac{1}{3}} W_{ih}^{\frac{1}{3}} W_{jh}^{\frac{1}{3}}}{\frac{1}{2}K_i(K_i-1)} \qquad 0 \le C_i^t \le 1 \tag{6}$$

Modularity: The clustering of the road freight transport network into a set of communities requires the partitioning of nodes (provinces) based on strong intra-community connections and relatively weak connections to nodes belonging to other communities. By applying community analysis to the road freight transport network, a group of provinces with strong freight transport relationships emerges. One of the metrics for partitioning nodes in the network is the community degree index, which is defined based on the difference between the actual number of links in a community and the expected number of random links in the network with the same degree. This index is defined in a directed network as follows:

$$Q_d = \frac{1}{2m}\sum_{ij}\left(w_{ij} - \frac{k_i k_j}{2m}\right)\delta(C_i, C_j) \tag{7}$$

where w_{ij} is the weight of the edges between nodes i and j, and k_i and k_j are the degrees of nodes ii and j, respectively. ci is the community to which node i belongs, m is the total weight of the edges, and $\delta(C_i,C_j)$ equals one if $C_j=C_i$, and zero otherwise (Newman, 2010).

In fact, this index measures the degree to which connected nodes in the network are separated into distinct clusters. In networks with low community structure, a disturbance in one part of the network can quickly spread to other parts, potentially leading to the collapse of a large section of the network. In contrast, networks with a high community structure have a useful ability to contain and mitigate disturbances within the network.

Closeness Centrality: Closeness centrality represents the sum of the shortest paths from a node (province) to other nodes (provinces) and considers the overall structure of the network instead of focusing solely on direct connections between a node and other nodes. This sum is calculated using the minimum path available among nodes, which is equal to $N-1$, and measures the spatial distance between a node and all other nodes in the network. Specifically, spatial distance in network analysis usually refers to the number of steps required for a node to reach other nodes in the network (Newman, 2010). When the distance of province ii is minimal, the province occupies the central position in the network, reflecting the maximum value of province i's closeness centrality. Thus, closeness centrality indicates a province's position in the road freight transport network in terms of the interconnectedness of transport relationships in the network and is calculated as follows, where d_{ij} is the distance (the number of steps required for a node to reach other nodes) between province ii and province j, and N is the total number of provinces in the network.

$$CC_i = \frac{N-1}{\sum_{j=1}^{N} d_{ij}} \qquad d_{ij} = \frac{1}{W_{ih}} + \frac{1}{W_{hj}} \tag{8}$$

that Betweenness Centrality: This index is defined as the ratio of the sum of the shortest paths between any two nodes that pass through a given node, reflecting the significance of a node as an intermediary that connects other nodes through paths (Newman, 2010). A province with the highest level of betweenness centrality serves as a bridge in the transportation flow, handling the greatest amount of freight transport, and plays a crucial role in the freight transport network.

$$BC_i = \frac{2}{(N-1)(N-2)} \sum_{j,k \in 1} \frac{\sigma(j,k \mid i)}{\sigma(j,k)} \tag{9}$$

where σ_j, k ∣ (i) represents the weighted shortest paths from nodes j to k that pass through node i, and d_{ij} is the sum of the shortest paths between nodes i and j, which can be calculated using σ (j,k) .

Eigenvector Centrality: In this index, the weight of a node's neighbors is not uniform, and neighbors that are more significant carry more weight in the computation of the centrality index. In many cases, the importance of a node in a network increase when it has connections to other nodes that themselves are important, which is the concept of eigenvector centrality (Newman, 2010). The primary focus in examining this index is the importance of a province's neighbors in the freight transport network, analyzing the role of neighboring provinces that share relationships. Provinces with higher eigenvector centrality are those that are connected to other provinces, which in turn have connections to numerous other provinces and hold significant importance in the road freight transport network, where λ is the largest eigenvalue of the adjacency matrix, ej is the eigenvector, and A_{ij} is the adjacency matrix.

$$EC_i = \lambda^{-1} \sum_{j=1}^{N} A_{ij} e_j \tag{10}$$

3.3 Data Analysis Methods

The first step in network analysis is the formation of the data matrix. For constructing and analyzing the freight transport network, data on the volume of freight transport between 31 provinces of the country was obtained from the Statistical Yearbook of 2023 published by the Transport and Transit Organization, presented in the form of a matrix. In this matrix, the nodes represent the provinces, and the edges represent the connections of outgoing and incoming freight transport. The rows in this matrix indicate the origin province of the freight, while the columns represent the destination province. The resulting matrix, which is essentially the adjacency matrix, indicates only the existence of a bidirectional freight transport relationship between two provinces. Thus, the entries of this matrix are either zero or one, representing the presence or absence of a relationship between the two provinces.

In this matrix, the edges between nodes can be considered as weighted or unweighted (binary), meaning that if only the existence or absence of a relationship is significant, a uniform weight can be assigned to all edges. However, if the intensity or weight of these edges—equivalent to the volume of freight transport between provinces—is important, a weighted network should be used. Therefore, since the existence of a relationship between provinces is not the only consideration in transportation, the volume of freight must also be taken into account. Because the amount of cargo transported between two provinces varies in value and meaning even if the tonnage is the same, a criterion should be considered as a weight index to reflect the intensity of relationships between nodes in addition to their existence. In this study, based on the available data and the importance of the volume of cargo dispatched from the origin province, inspired by the work of Deguchi et al. (2014), the following index has been used as a weight index in the transport matrix, where t_{ij} is the amount of cargo transported from province ii to province j and T_i is the total cargo of province i.

$$w_{ij} = \frac{t_{ij}}{T_i} * 100 \tag{11}$$

After constructing the weighted matrix, the next step is to form the weighted adjacency matrix (W) by multiplying each entry of the weighted matrix by the adjacency matrix. This weighted adjacency matrix will serve as the basis for calculating network metrics and analyzing its structure.

In Iran's road transport network, nearly all 31 provinces exchange cargo with one another; however, a substantial portion of these exchanges carries very minimal weight and does not constitute a structurally "meaningful connection." This situation results in an almost fully dense network (density $\approx$ 1), which distorts centrality analysis and cluster detection because very weak links contribute equally to the analysis as stronger links.

According to Duenas & Fagiolo (2013), when the initial network is nearly complete, the most appropriate method to preserve the meaningful structure of the network is to set the threshold equal to the initial network density. This removes links that do not play a structural role and retains only those relationships that meaningfully contribute to flow intensity. Thus, in the present study, considering the computational density coefficient of 0.999 in the initial state (complete connections), all connections below this coefficient in the network are considered zero. Therefore, Within the methodological framework of this study, the threshold value is not an exogenous or arbitrary parameter; rather, it is determined endogenously in a data-driven manner based on the actual network density and is calculated and applied by the Gephi software. This approach is consistent with the complex network literature and is commonly employed when the objective is to extract the structural core of the network and eliminate noisy or low-importance links.

After weighting the edges and applying a zero relationship to weak edges, the network clusters are localized based on the modularity degree. The grouping of the road freight transport network into a set of communities requires the division of nodes (provinces) with high-intensity intra-community links and relatively weak connections with nodes belonging to other communities, such that the modularity degree index divides the nodes (provinces) into main clusters. After grouping the communities in the network, the main hubs are identified and selected from each community based on the most suitable network indices.

4. Results

Based on the calculations performed using Gephi software, the number of clusters identified according to the community degree index after applying the threshold in the freight transport road network in Iran is four. According to the graph below, the first cluster includes the provinces of Hormozgan, Fars, Yazd, Kerman, Bushehr, and Kohgiluyeh and Boyer-Ahmad. The second cluster comprises Tehran, East Azerbaijan, Gilan, Alborz, Markazi, West Azerbaijan, Qazvin, Hamadan, Qom, Kurdistan, Zanjan, and Ardabil. The third cluster consists of Isfahan, Khuzestan, Kermanshah, Lorestan, Chaharmahal and Bakhtiari, and Ilam. The fourth cluster includes Razavi Khorasan, Mazandaran, Sistan and Baluchestan, Semnan, Golestan, South Khorasan, and North Khorasan.

The size of each node in the graph reflects the importance of that node (province) within the network, and the thickness of the edges (connections) between two nodes indicates the strength of their interaction. In other words, the greater the importance of a province in the network structure, the larger its node appears; and the stronger its connections with other provinces, the thicker the corresponding edges will be.

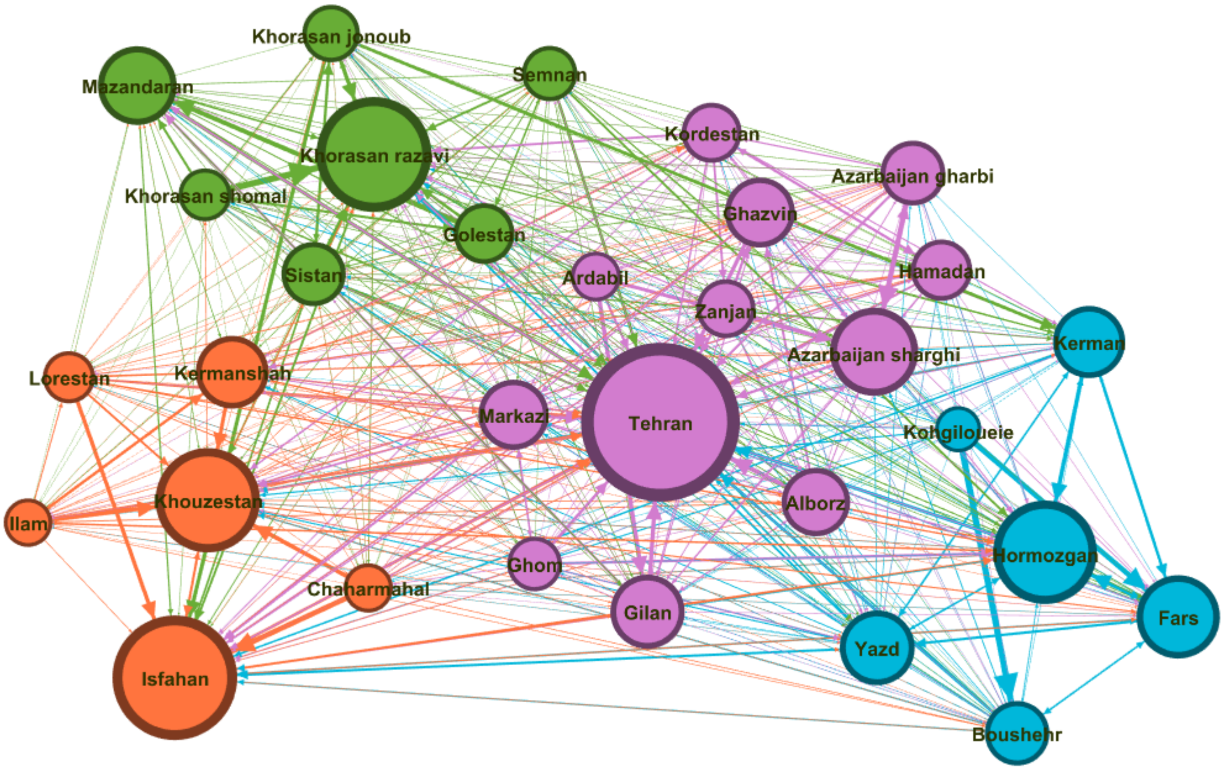

Figure 3. Graph of Clusters in the Freight Transport Road Network

Table 1. The Network Metrics of the Freight Transport Road Network

Privence	Modularity	Node Degree	Node Strength	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality	Clustering
Bousher	3	33	159.65	0.7895	0.0083	0.41259	0.696667
Fars	3	45	225.82	0.6977	0.02626	0.96881	0.634236
Kerman	3	34	186.35	0.625	0.00677	0.82877	0.74026
Kohgiloueie	3	10	95.32	0.5769	0.00023	0.09748	0.857143
Hormozgan	3	47	297.15	0.6977	0.01247	1	0.614943
Yazd	3	47	195.86	0.8108	0.02539	0.87558	0.664021
Tehran	2	55	491.64	0.8571	0.03561	1	0.605747
Azarbayejan Sharghi	2	49	242.77	0.7692	0.01606	0.97407	0.664021
Markazi	2	46	179.87	0.7692	0.01241	0.87301	0.690883
Gilan	2	47	193.88	0.7692	0.01482	0.93075	0.698462
Hamedan	2	38	148.44	0.7692	0.01173	0.63174	0.727273

Table 1. The Network Metrics of the Freight Transport Road Network (Continued)

Zanjan	2	35	139.95	0.7692	0.00506	0.50768	0.774704
Alborz	2	45	173.65	0.75	0.01285	0.90936	0.693732
Azarbayejan Gharbi	2	42	160.49	0.7317	0.0156	0.86161	0.725296
Ghazvin	2	41	179.16	0.7317	0.00569	0.80901	0.73
Qom	2	34	125.23	0.7317	0.0043	0.59806	0.785714
kordestan	2	31	143.84	0.6977	0.00166	0.5259	0.819048
Ardebil	2	23	108.43	0.6818	0.00044	0.30777	0.9
Khozestan	1	57	299.82	0.9677	0.06528	0.96736	0.603448
Isfahan	1	52	371.29	0.7895	0.0278	1	0.609195
Kermanshah	1	41	188.4	0.7143	0.01109	0.81325	0.728333
lorestan	1	29	115.96	0.7317	0.00286	0.38774	0.780952
Chaharmahal	1	21	106.06	0.6522	0.0016	0.27295	0.783088
Ilam	1	22	103.14	0.6977	0.00124	0.20888	0.833333
khorasan Razavi	0	51	336.95	0.7692	0.02996	1	0.610345
Mazandaran	0	48	209.7	0.8333	0.02166	0.87138	0.685185
Semnan	0	35	127.28	0.7692	0.00941	0.46826	0.715
Sistan	0	33	158.47	0.6818	0.00673	0.62371	0.731602
Golestan	0	32	146.39	0.75	0.00537	0.40221	0.728261
khorasan Jonobi	0	21	134.8	0.5769	0.00181	0.43211	0.761905
Khorasan Shomali	0	20	118.38	0.625	0.00189	0.23678	0.779167

Source: Output from Gephi software

Table 1 presents the network metrics of the freight transport road network, categorized by each metric and province. In Community 3, Hormozgan Province stands out as significant in terms of degree centrality, intensity degree, eigenvector centrality, and clustering coefficient. This indicates that Hormozgan Province holds a high importance regarding the number and intensity of transport connections with other provinces and also has relationships with provinces that themselves have numerous high transport connections.

Fars Province is also prioritized in this cluster based on intermediary centrality, serving as a bridge in the transport flow, acting as an intermediary between other provinces. Yazd Province has the highest closeness centrality among the provinces in this cluster, reflecting its position in the freight transport road network regarding the interconnectedness of transport relationships.

Considering that the clustering coefficient focuses on the strength of connections between provinces and their multilateral relationships while also measuring a province's inclination to establish more connections with other provinces, this indicator was considered the final criterion for hub selection within each community, provided that the other centrality measures were sufficiently high. Therefore, Hormozgan Province, with the lowest clustering coefficient, is identified as the selected hub in this cluster, although it also holds special importance in the other three metrics.

Based on the aforementioned metrics, in Community 2, Tehran Province is recognized as significant in the freight transport network across all derived metrics, given that this province holds a more favorable position in all indicators, it is designated as the selected hub within this community.

In Community 1, Khuzestan Province is noted for its significance in the metrics of degree centrality, closeness centrality, and clustering coefficient, while Isfahan Province is important in terms of intensity degree and eigenvector centrality. Considering the criterion of having the lowest clustering coefficient in each cluster, Khuzestan Province is identified as the selected hub in this cluster.

Among the provinces in Community 0, Razavi Khorasan Province is identified as one of the strong nodes in this cluster based on the metrics of degree, intensity degree, betweenness centrality, eigenvector centrality, and clustering coefficient. Mazandaran Province also holds the highest closeness centrality. Given the low clustering coefficient of Razavi Khorasan Province, this province is designated as the hub of this cluster.

The use of the clustering coefficient as a final criterion for hub selection is grounded in complex network theory, as this metric measures the tendency of a node to form multilateral connections and local loops, indicating the extent to which the node is part of a closed local network or, conversely, serves as a “boundary” or “open” node connecting its community to other parts of the network. In network science, nodes with the lowest clustering coefficients are often the ones that function as “gateways” or “distribution hubs,” facilitating connections between clusters or different regions (Newman, 2010; Barabási, 2016). Since the objective of logistics hubs is aggregation, distribution, and inter-regional connectivity, nodes with lower clustering are naturally less constrained by local cohesion and are better positioned to serve as national hubs. However, hub selection was based on nodes with the lowest clustering coefficients and the highest centrality measures.

5. Conclusion

Based on the results obtained from the hub location analysis of road transport in Iran using network analysis methods, the number of communities identified according to the community degree index is four, as follows:

Community One: Includes 6 provinces: Hormozgan, Fars, Yazd, Kerman, Bushehr, and Kohgiluyeh and Boyer-Ahmad.

Community Two: Includes 13 provinces: Tehran, East Azerbaijan, Gilan, Alborz, Markazi, West Azerbaijan, Qazvin, Hamadan, Qom, Kurdistan, Zanjan, and Ardabil.

Community Three: Includes 6 provinces: Khuzestan, Isfahan, Kermanshah, Lorestan, Chaharmahal and Bakhtiari, and Ilam.

Community Four: Includes 7 provinces: Razavi Khorasan, Mazandaran, Sistan and Baluchestan, Semnan, Golestan, South Khorasan, and North Khorasan.

Based on the optimal computational indices from the Gephi software, Hormozgan, Tehran, Khuzestan, and Razavi Khorasan provinces have been identified as the selected provinces for hub establishment.

The identified hubs from the network analysis method are geographically diverse across various regions of the country and adequately consider the proximity criteria of the hubs and clusters, taking into account distance and the volume of bilateral freight exchanges. Given the results obtained, and considering that the network analysis method accounts for all direct and indirect transport connections of the provinces within a binary network, as well as that most centrality metrics and clustering coefficients confirm the identified hubs, the results are quite acceptable.

This study has several structural limitations that should be considered when interpreting the results. First, although the research reveals the actual structure of Iran's road transport network using network analysis, it relies on data from only the year 2023. While network studies suggest that centrality and clustering structures remain stable over the long term, a multi-year analysis could further strengthen the temporal robustness of the findings.

Second, the current network model does not incorporate operational constraints such as terminal capacities, infrastructure costs, travel times, or geographic limitations. Finally, the findings of this study are best used as a structural framework for identifying key nodes, and final policy decisions should be complemented with additional engineering, economic, and environmental assessments.

Considering the unsuccessful experiences of the country regarding the establishment of logistics centers and similar infrastructures, it can be claimed that developing these centers faces fundamental challenges. The first challenge in this regard is the approach and perspective of governance concerning these centers. Logistics centers, because their establishment and operation require significant investment and have a cross-sectional nature, necessitate support and guidance from the public sector.

The most significant challenge is the lack of a specific authority for the development of these centers. The presence of supervisory and executive agencies, along with multiple stakeholders in the cargo transport and transit sector, leads to time wastage and ineffective decision-making. Each of these agencies, possessing various laws and regulations that sometimes conflict with one another, creates confusion for domestic and foreign private sector stakeholders.

Given the network-oriented nature of this study and its contribution to identifying the real structure of freight flows and central hubs, several research paths can further extend this line of inquiry. First, future studies are encouraged to employ temporal network analysis to examine the stability of clusters and hubs over multi-year periods, thereby revealing the temporal dynamics of the network and the effects of economic or infrastructural shocks. Second, integrating network analysis with multi-objective mathematical optimization models (e.g., cost–time–emissions) could provide a comprehensive framework for the operational design of hub networks and facilitate implementation-oriented decision-making.

Third, extending the research toward the analysis of infrastructure-development scenarios—such as constructing new highways, modifying transit corridors, or establishing border terminals—would enhance the predictability of network-level impacts. Fourth, incorporating detailed data on travel time, network capacity, energy constraints, and traffic congestion alongside the freight-flow matrix could elevate the model from a structural level to an operational one. Finally, it is recommended that the findings of this study be used as inputs for designing smart logistics systems and developing national-level network-monitoring dashboards, enabling policymakers to monitor and manage hub performance and freight flows in real time.

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