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Analysis of the Iranian Airport Network by a Complex Network Approach

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ABSTRACT

In every country, airports are among the most important air transport systems in that country. When an aircraft flies from one airport to another, it creates a graph that can be completed with information about each flight, such as the number of flights per path, the number of passengers, traffic load, and so on. In the present paper, the airports of Iran and the domestic flights are considered as a network and the structure of the network is analyzed, and then the measures of complex networks such as degree distribution, shortest path length, analysis of centralities, clustering coefficient and their correlation and the way these centralities behave are examined. This analysis shows the Iranian Airport Network (IAN) that has a degree distribution described by the power function. The average path length in this network is 1.9, and the average clustering coefficient is 0.69, which meets the characteristics of a small-world network and is also considered an example of a disassortative network. The purpose of this research is to investigate the network of airports in Iran, which is ultimately important for the expansion of airports, and also to identify the important points of airports.

Keywords: ***Complex Network; Iranian Airport Network; Centrality; Correlation.***

1. Introduction

The network structure has been considered since the "Quantitative Revolution" of the 1950s [1]. Today, the analysis of complex networks plays an important role in scientific investigations of all types of networks, including the analysis of neural networks [2], the analysis and prediction of critical illnesses [3], the analysis of images [4], or the analysis of national airport networks. In recent years, there has been a growing interest in Graph Theory in complex networks since many analyses and even predictions and trends can be obtained through the analysis of complex networks [5-8].

An Air Transport System (ATS) is of particular social, economic, or military importance to every country. Changes in this system might be complicated, and any minor change in the network may cause a general change in network structure. Also, network growth can create a new network with new specifications. When a complex network becomes larger, new nodes are more likely to connect to the existing nodes [9]. Moreover, nodes with the most connections tend to further strengthen themselves [10]. Advances in complex networks have increased the interest in airport systems [11-15].

When investigating airports and air transportation systems, considering the issue to which airports any given airport tends to connect is of strategic importance both socially and economically. Thus, previous studies have used complex network measures to analyze the air transport networks of different countries and their airlines, including the US [11], China [12], Brazil [16], Italy [17], India [14], Australia [18] and Lufthansa Airlines [19]. These analyses can be useful for the ATS networks of any country and will have some practical implications for future air transportation plans that may use this analysis as required.

Complex networks convert the structure of airports and flight paths into a graph, in which airports are considered as vertices and flight paths as inter-airport links. These graphs can display different behaviors and characteristics, but it is interesting to note that each of these structures has one of these two structural features, i.e., small world or scale-free. The characteristic of the small world network is defined by the average path length, indicating the average distance of each pair of nodes, so that it slowly increases with the size of the network (N) [6].

$$L \propto Log\ N \tag{1}$$

In the scale-free property, the degree distribution of the network follows the power law [10]. The easiest way for the structural expression of this type of network is to consider a model in which $p(k) \sim k^{(-\gamma)}$ [20], this means that the probability of finding a high-degree node is relatively small in comparison with the high probability of finding low-degree nodes. The most popular example of this model is a model introduced by Barabási and Albert [9]. Using the concepts of SF and SW for analyzing air transportation networks, some studies have been conducted that included the World Airport Network (WAN), which has been studied from both topological and dynamic traffic viewpoints [21]. According to an analysis of the WAN network, Guimera et al. concluded that WAN is an SW network [13]. Specifically, the theory of complex networks offers a set of new analytical methods for spatial economic analysis to provide this new insight [19].

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2. Literature Review

Network structures exist in a variety of contexts such as neural networks, transport networks, and social phenomena, to mention a few, these structures are obtained according to network metrics, the number of metrics is analyzed, and the network behavior is identified. Any particular type of network offers certain topological properties which specify a network's connectivity, interactions, and dynamic processes [22].

Network structure analysis is important because it allows us to identify efficient methods for network structure engineering, after which we can identify those poorly connected nodes, and also, we can develop a systematic method to identify the most important central nodes or vital nodes on the network, whose roles are very critical and if these nodes are in danger, this can be dangerous to the entire airport network structure [18].

Network properties can be obtained using metrics in the network, using appropriate measurements, network structure and features, and statistical properties [20]. The IAN structure and features are then evaluated using appropriate measurements. According to the topological characteristics, the properties of different types of networks are shown in Figure 1. A regular network is a graph in which each vertex is exactly connected to the same vertex of its neighbor as Ring Networks. Random networks are constructed by randomly adding several edges between the nodes and they prevent the formation of multiple edges and loops. A small world network is one of the regular and random networks that have a short path length and a high clustering coefficient that one can reach other vertices through a few short steps. Scale-free and Real-world networks exhibit features like those of the small world, except that their degree distribution graphs are somewhat different. Many experimental graphs are well designed using SW networks, while many real-life domains such as roads, electricity power networks, and genes display their network-specific features.

Since airport networks can be considered as a graph or network, we can also form a graph of the airport network in Iran and survey it. Reviewing and analyzing the graph of the country's airports network can be very important for the development and review of the airport infrastructure as well as the identification of important airports in terms of security.

3. Methodology

The methodology of this research consists of four stages, which are data collection, data pre-processing, data analysis. In the rest of this section, each stage will be briefly introduced.

3.1. Data collection

Iran has an area of more than 1.6 million km2 with a population of more than 80 million people. Roads, railways, and air routes are the common means of transportation among the public. In Iran, people are less likely to use air transportation, however, Iran has 68 airports, most of which are located in the coastal areas of northern Iran and coastlines in southern Iran, and there are a total of 208417 flights across the entire Iranian airline, with more than 23 million passengers annually being transported through airlines. Given this volume of human transport as well as the strategic position of Iran in the Middle East, the study of Iranian airports can be useful. Air network analysis can provide a proper understanding of the future development of airports and can also provide an important source of information for network policymakers. The IAN includes domestic and international airports that have regular flights. The air transport data of Iran used here belong to the year 2017-2018, received from the country's airline organization (https://caa.gov.ir/air-transport-annual-report).

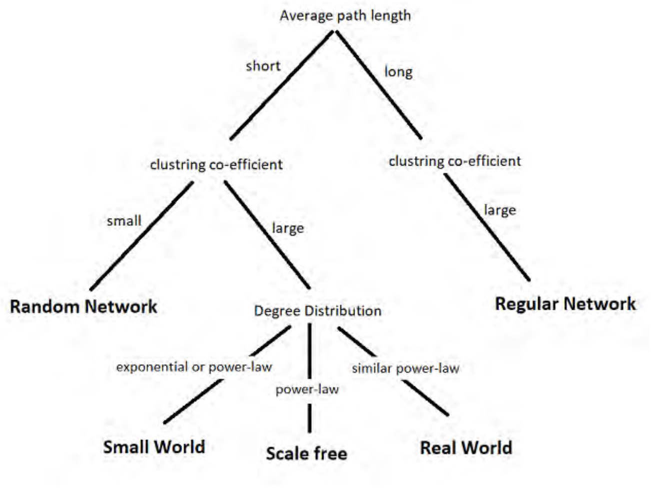

Figure. 1. The tree diagram representing the features of different types of networks.

3.2. Data pre-processing

To study the IAN, each flight that connects to two airports forms an edge between those two airports, which is a directed edge with a specific origin and destination. Each of the 68 existing airports is considered a set of vertices and the inter-airport flights are regarded as a set of edges forming a graph. This graph can be either unweighted or weighted. The unweighted graph has been specified only with the paths between the two vertices and the weighted graph has been specified with the traffic load and the number of paths between the two vertices.

The intended graph is specified with $G=(V,E)$, where V is the set of vertices for the network (n is the number of vertices), which involves $V=\{v_1,\dots,v_{68}\}$ and E the set of edges that includes 499 directed flights. The unweighted graph of this network is represented by an A_{n*n} matrix in which $a_{i,j}=0$, which means that there is no flight between the two airports, and if we have $a_{i,j}=1$, it means that there is a direct flight between airports i and j [23], and this airport can be represented with an A_{68*68} matrix that has only 499 elements with value 1. The weighted graph of this network is specified with an A_w matrix, with each $w_{i,j}$ element indicating the total number of flights from the airport to. The IAN is shown as a complex network in Figure 2, in which the airports are represented by solid circles, and all the existing routes are represented by the edges. Moreover, the IAN shown in Figure 3 is displayed based on the number of flight-outs on the map of Iran. Table 1 shows air traffic volume-ins and volume-outs and the number of flight-ins and flight-outs in the top 15 cities in 2017-2018, indicating that Mehrabad Airport of Tehran has the highest number of flights and the highest number of passenger transports among the other airports in the country. Table 1 shows that the number of flight-ins and flight-outs as well as the number of passengers

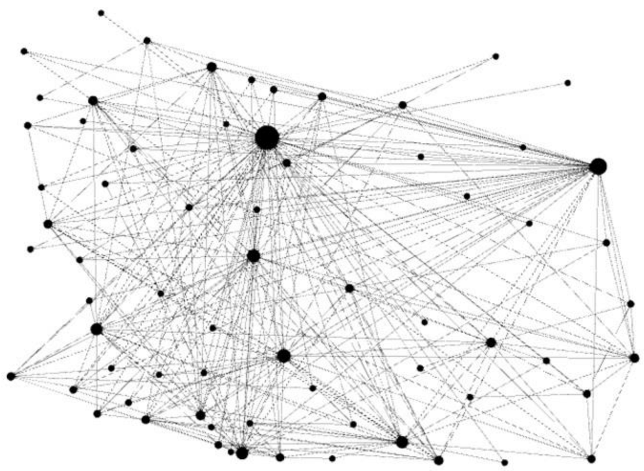

Figure. 2. AIN as a Complex Network

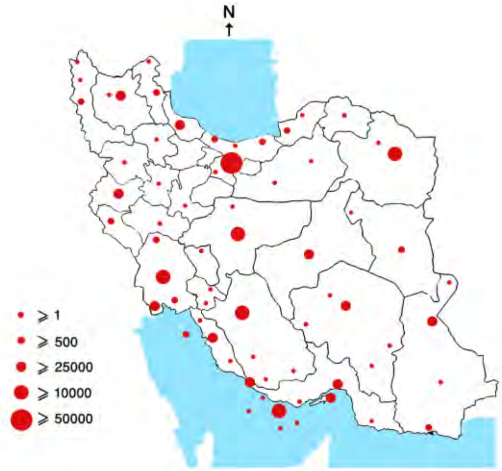

Figure. 3. The Number of Flight-outs in Iran in 2017-2018

Table 1. Top 15 cities by the number of routes.

Rank	*City*	*Out-Degree*	*In-Degree*	*No. of flights out*	*No. of flights in*	*Volume-Out*	*Volume-In*
1	MehrAbad	62	64	71748	71744	8406114	8441921
2	Mashhad	37	38	31489	31522	4170777	4262063
3	Shiraz	26	28	15500	15509	1504668	1536227
4	Esfahan	25	25	10061	10253	1079255	1089402
5	Kish	23	22	11581	11603	1373812	1372499
6	Ahwaz	22	20	11721	11713	1344241	1325976
7	BandarAbbas	22	22	5518	5521	618776	605200
8	Kerman	13	15	2942	2964	390651	387081
9	Qeshm	13	11	2351	2355	241786	234507
10	Tabriz	13	12	6503	6509	792231	781118
11	Khalij-Fars	12	14	3271	3271	416383	417832
12	Rasht	12	15	2284	2289	216965	213312
13	Bushehr	11	8	2270	2262	257823	250324
14	Zahedan	11	13	2266	2196	255836	252066
15	KermanShah	10	11	2925	2932	325976	324532

arriving are not much different from the number of passengers leaving, but it is noteworthy that the number of passengers who arrive in the 4 top cities through the airlines is higher than the number of passengers who depart; however, in most of the lower-ranking cities, the number of passengers who depart is higher than the number of passengers arriving, thus it can be concluded that the cities of Tehran, Mashhad, Shiraz and Isfahan receive more guests than other cities.

3.3. Data Analysis

Data analysis included analysis of degree, average shortest path length and clustering coefficient, centrality measures, in the following, each analysis will be reviewed.

3.3.1 Analysis of Degree

The average degree and first-order distribution provide a general picture of the overall structure of the network. The average degree in the IAN network is 7.33 and the highest degree is 62, which belongs to Tehran airport. In the analysis of the IAN network, the number of nodes in a network is shown with k_i , the degree of a node is represented with n , and the existence of the connection between the nodes i and j are indicated with $a_{i,j}$, and the weight of the edge between the nodes i and j with $w_{i,j}$. In a network with n nodes, if the number of nodes with k degree is assumed as n_k, then the degree distribution and the degree distribution curve are obtained from the following equations:

$$p(k) = \frac{n_k}{n} \qquad (2)$$

$$p(>k) = \sum_{k'=k}^{\infty} p(k') \qquad (3)[24]$$

3.3.2 The average shortest path length

In an undirected network, the shortest path distance $d(u, v)$ is the number of links in the shortest path between the nodes u and v in the network [25]. In Graph Theory, the directed distance $\overleftarrow{d}(u, v)$ between a pair of nodes *u* and *v* in a directed network is considered to be the length of the directed shortest path from *u* to *v*. In the case of there not being a directed path connecting two nodes, the corresponding distance is considered to be infinite. It is straightforward to realize that in general, $\overleftarrow{d}$(u,v)= $\overleftarrow{d}$(v, u).

The average shortest path length determines the convenience of traveling on a network as it quantifies the efficiency of the network in sending information (traffic mobility) between vertices [20].

Average path length (L) is determined as the average number of edges along the shortest paths for all possible node-pairs in the network [6], written as:

$$L=\frac{1}{n(n-1)}\sum_{i\neq j} d_{ij} \tag{4}$$

3.3.3 Clustering coefficient analysis

The clustering coefficient *(Ci)*, calculates the local cohesiveness of a node *i* and also shows the network's transitivity, written as:

$$C_i=\frac{1}{k_i\left(k_i-1\right)}\sum_{j,k_j} a_{ij}a_{jk}a_{ik} \tag{5}$$

The clustering coefficient in an airport network captures the probability that two airports connected to a third one is also directly connected. A larger C_i value means that the node has a more compact system of connections with its neighbors. In a fully-connected network, the C_i of all nodes equals 1. C_i of nodes with $k_i=1$ equals 0.

Each weighted clustering coefficient (C_i^w) captures local cohesiveness by considering the interaction intensity present on the local triplets [26, 27]. The weighted clustering coefficient of the network (Ci) is calculated as the average of all the individual Ci^w, written as:

$$C_i^w=\frac{1}{k_i\left(k_i-1\right)}\sum_{j,k}\frac{1}{<w_i>}\frac{w_{ij}+w_{jk}}{2}a_{ij}a_{jk}a_{ik} \tag{6}$$

3.3.4 Centrality measures

Centrality measures the relative importance of a node within a network like being directly connected to others, being accessible to others, and being the intermediary between others. Infrastructure analysis to determine the characteristics of a network is obtained from the centrality concept assessed by various metrics. The s_i and $k_i$indicate the local importance of a node, however, local measures do not take into account the non-local effects, such as the existence of bottlenecks nodes, which have small degrees but act as bridges between different parts of the network. In this section, three indices, namely, degree centrality, closeness centrality, and betweenness centrality, are considered to measure the importance of a node.

Degree centrality specifies that each node is directly connected to other nodes which can determine the importance of a node in the network [28, 29]. As previously investigated, the degree centrality is obtained from the following equation.

$$C_D(i)=\sum_{j=1}^{n} a_{ij} \tag{7}$$

In the above formula, the $a_{ij} \neq a_{ji}$ relation can be correct. For the same reason, we usually have two kinds of definitions for the degree, in-degrees, and out-degrees. In-degree is the count of edges directed into a vertex and the out-degree is the count of edges directed out of a vertex. In the IAN network, the in-degrees are approximately equal to the out-degrees, and this has caused the network to be symmetrical just like the ATNC network [30].

Closeness centrality specifies the closeness of a node on the shortest possible path to other nodes, and determines the access rate of a node in zthe network [28, 31, 32], which is obtained from the following equation:

$$C_c(i)=\frac{(n-1)}{\sum_{v_i\in n, i\neq j} d_{ij}} \tag{8}$$

Betweenness centrality identifies which particular node is most commonly found among the nodes in the network [33]. A node in the network can be more important if it lies on the shortest paths among pairs of other nodes [29, 33]. The betweenness of each node is defined by all the nodes passing through that node and is obtained from the following equation:

$$C_{\overline{B}}(i)=\sum_{i\neq j\neq k}\frac{\sigma_{kj(i)}}{\sigma_{kj}} \tag{9}$$

Where σ_{kj} calculates the sum of shortest paths from node *k* to node *j*, and $\sigma_{kj}(i)$ calculates the number of those paths that pass-through node *i*. The nodes that are most frequently found between the shortest paths in a network have greater betweenness.

4. Results

The graph of the degree distribution curve is shown in Figure 4. According to the function obtained in the Figure 4, the degree distribution follows the Power Law, which has attracted great attention in scientific resources and even popular resources [9, 24, 34-37]. In the degree distribution of IAN, the number of routes per airport decreases rapidly because most airports have less than 5 routes and only a few airports have many routes. For instance, Tehran Airport is connected to 62 airports from among the 67 possible airports.

It is specified that the weights of individual links do not provide a general picture of a network's complexity [38]. For this reason, we considered the node strength (S_i) in the network for further investigation of the network. In the present paper, we assumed the number of flights from an airport as the node strength, which has a very high correlation with the nodes. Figure 5 shows that in the IAN, there is a very close relationship between the number of nodes and the number of flights in that node. As it is known, a larger airport has more flights. S_i is obtained from the following equation:

$$S_i = \sum_{j=1} a_{ij} w_{ij} \qquad (10)$$

In Table 2, the equations of Figures 4 and 5 have been shown.

In the IAN network, one can move from any airport to any other airport through Mehrabad Airport, hence, Mehrabad Airport can be considered the central node [25]. Only three airports, i.e. Kashan, Lamerd, and Abu Musa airports, are not linked to Mehrabad on this network. This has caused the network's diameter to be equal to 3, emphasizing that eventually a passenger can be moved to another airport by 3 flights from each airport.

For further analysis, the IAN network is compared with two networks, namely Erdos and Rienyi's random network [39] and the small world of Watts and Strogatz [6]. In this comparison, for the SW network, a lattice with 68 nodes is considered, each node is linked to 4 nodes from its closest neighbors, so each link is rewired with the probability of $p = 0.15$ and limitations for loop edges and multiple edges. Then some of the links are omitted until they eventually match the number of IAN links. The values of the average shortest path length for random networks and small-world networks were obtained after 10 runs, and the obtained means were then compared. The average path length obtained for the random network of the same size and specifications is equal to $L_r=1.62$, which is smaller than the average path length obtained for the IAN network and the value obtained for the SW network is equal to $L_{sw}=2.9$, a value which is greater than the value obtained for IAN network. The average length obtained as $L_{AIN}=1.9$ indicates that, on average, one can go from the source airport to the destination airport with 2 flights. Table 3 compares the structural characteristic of IAN with similar networks.

For further analysis, the clustering coefficient in the IAN network has been compared with the clustering coefficient in the random network and SW network. The clustering coefficient in the IAN network is $C_{AIN}=0.69$, which is much larger than Erdos and Rienyi's random network with the same size and characteristics ($C_r=0.107$) and is close to the clustering coefficient in the SW network (C_{SW}=0.46). The probability that the neighbors of an airport in the IAN will be directly connected is about 0.7, which has led passengers to have more access from one airport to another. To examine the effect of information about the weighted network on the clustering coefficient, we defined the weighted clustering coefficient (C_i^w) for the combination of the structure and the weight of the network.

The average C_i^w for all nodes in the IAN network is 0.44, which is less than its unweighted counterpart. This fact $C^w < C$ indicates that IAN has more traffic on the hubs, and there is more traffic in places where we have no triplets. A comparison of the clustering coefficient for airports in different countries is shown in Table 3.

4.1. Statistical distribution

The distribution of the centrality indices is shown in Figure 6. The degree centrality index in the IAN network follows the power law, with R^2 greater than 0.93. Since more than 52 percent of the air paths are available to 10 airports in the IAN network, the degree centrality curve demonstrates that several nodes carry most of the IAN paths and nearly 60 percent of the nodes carry only 1 to 4 paths. According to Figure 5, the closeness curve has the flattest shape than the betweenness and degree curves. This flatness in the curve suggests that the variations in closeness values are not as large as changes in-betweenness and degrees, and most cities have a high degree of accessibility, so only the city of Abu Musa, which is among

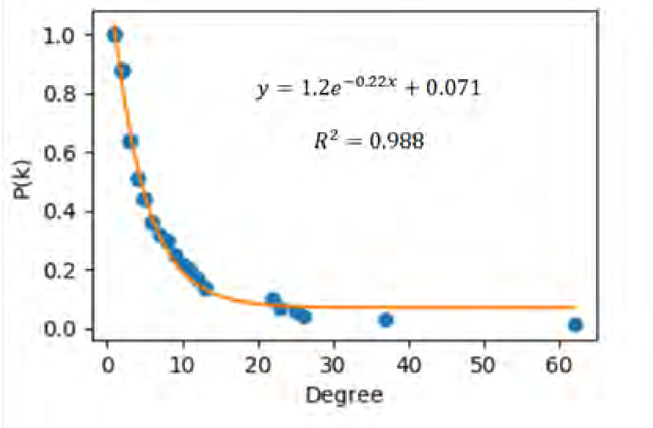

Figure. 4. Degree distribution

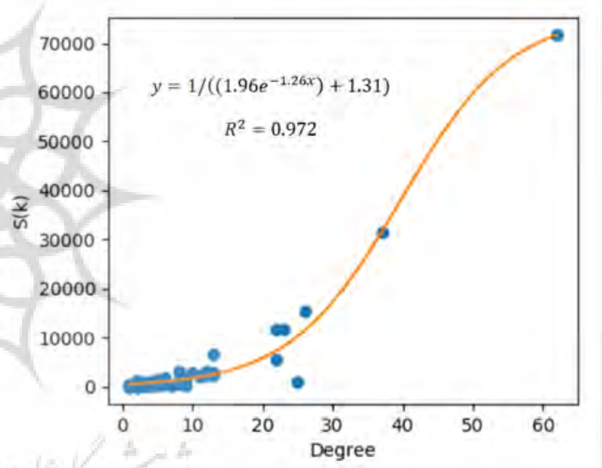

Figure. 5. . S_k as a function of degree k

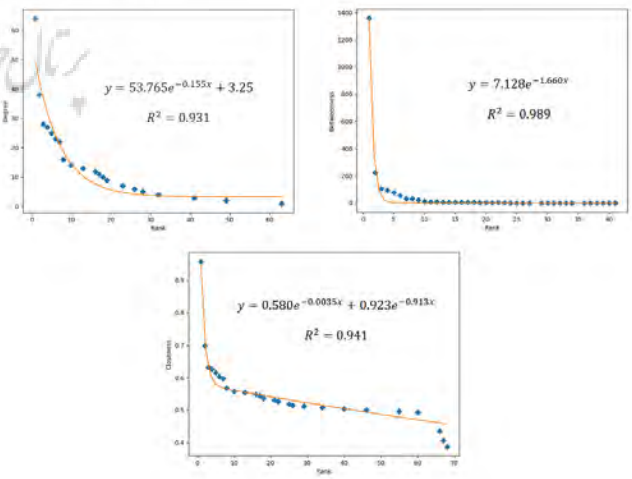

Figure. 6. Statistical distributions of degree, betweenness, and closeness.

Table 2. The best fitting models for degree distribution and $s(k)$.

	Function	*a*	*b*	*c*	R^2
Figure 3	$y = ae^{bx} + c$	1.2	−0.22	0.071	0.987
Figure 4	$y = 1/((ae^{bx}) + c)$	1.96	−1.26	1.315	0.972

Table 3. Characteristics of air transport networks of Australia and other countries/regions

Country	*# nodes (n)*	*# edges(e)*	*Average degree ⟨k⟩*	*Average path length (L)*	*Clustering coefficient (C)*	*Type of Network*
India	79	455	11.52	2.26	0.66	SW
World	3883	27051	13.93	4.4	0.62	SF SW
Italy	50	310	12.4	1.98~2.14	0.07~0.1	SF SW Fractal
US	272	6566	48.28	1.84~1.93	0.73~0.78	SW
China	144	1018	14.14	2.23	0.69	SW
Australia	131	596	9.1	2.9	0.5	SW
Iran (this paper)	68	499	8.2	1.9	0.69	SW

the marginal cities, has a value of less than 0.4. The betweenness curve graph shows that the highest transport passes through Mehrabad Airport, while 41% of IAN's airports have a value of 0. A sharp drop in the slope of the betweenness curve with a high value of $b = -1.66$ suggests that to pass from one airport to another, only one airport plays a critical role, and in the absence of this airport, most of the inter-airport paths would disappear. The importance of Mehrabad airport was so high in the betweenness curve that it caused us to conduct another experiment. Hence, the IAN network was reinvestigated without considering Mehrabad airport, and some of the key network values were re-calculated which led to interesting results. In the network without Mehrabad airport, the length of the shortest paths which was 1.9 increased to 2.34, the network diameter increased from 3 to 6, and the average clustering coefficient reduced from 0.69 to 0.42, indicating the high importance of Mehrabad airport in the IAN network.

Figure 7 represents the spatial distribution of three centralities. According to the figure, the degree of centrality is scattered across the central regions, but in the southern regions, it is found as high values. Also, the highest closeness is found in the southern regions, including the islands and southern ports of Iran; and in the northern regions of Iran, the closeness values have higher density, whereas lower values are seen for betweenness in the northern regions of the country, with the higher values belonging to the southern areas. In the west of the country, only the Ahwaz node has a high betweenness value, but in the north, there is no high value; in the east, the cities of Mashhad and Zahedan have a high betweenness value. As is seen in the spatial distribution, Tehran has the highest values for the distribution of all three centralities.

4.2. The relationships among the centralities

Table 4, shows the top 15 cities based on closeness, betweenness, and degree. According to this table, Mehrabad and Mashhad airports rank first and second in all three centralities. All the airports have the same rank for closeness

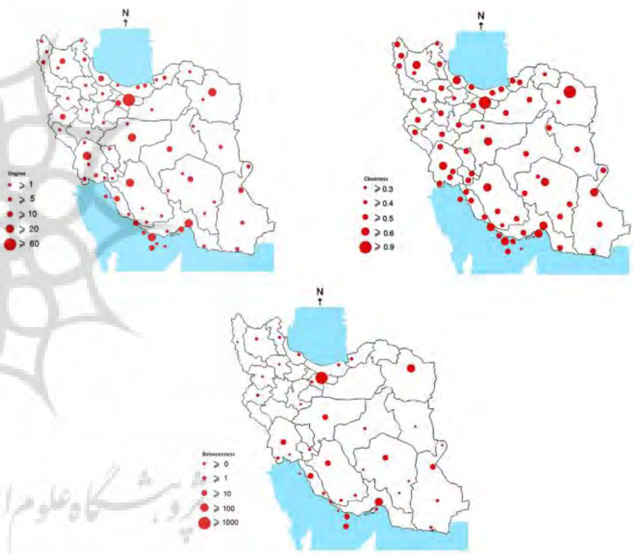

Figure. 7. Spatial distributions of degree, closeness, and betweenness.

and degree, indicating the perfect correlation between degree and closeness, but this is not the case for closeness, so Shiraz has the third rank for degree and closeness, but it has the fourth rank for betweenness. Bandar Abbas has fifth place in degree and closeness, but it has third place in-betweenness. Also, Siri port does not exist in the two top centralities of degree and closeness, but in-betweenness it ranks seventh, suggesting the importance of this node on the southern coast of Iran. According to the airports existing in degree and closeness and their ranks in-betweenness, a high degree of non-correlation between degree and closeness centralities with the betweenness is seen. Given the closeness and degree values in Table 4, most of the central cities and hubs are connected and have high closeness to reach each other. In terms of betweenness values, Bushehr, Zahedan, Bandar Abbas, and Siri airports, which are located in marginal areas and southern Iran, have a higher level than the degree and closeness centralities. Also, Shiraz, Isfahan, Kerman, Rasht, Qeshm, Persian Gulf and Tabriz airports have lower ranks than the Degree and Closeness Centers. Concerning the high correlation observed in Table 4, it is necessary to examine the correlation among the centralities; these correlations are shown in Table 5. The high correlation values indicate a significant level of consistency in the connections among the IAN nodes

4.3. Analysis of Degree Correlation

Degree correlation shows the average degree of neighboring nodes. In a network, if nodes with the highest degree, or so-called hubs, tend to connect, it is said that the network is assortative, and if nodes with high degrees tend to be connected to low-degree nodes, the network is called a disassortative network [10]. If V_i is the sum of vertices of v_i neighbors and k_i is the number of neighbors, the average degree of V_i is defined as follows:

$$K(i) = \frac{1}{k_i} \sum_{v_j \in V_i} k_j \tag{11}$$

For the IAN network, the relationship between $K(i)$ and degree, as shown in Figure 8, is equal to $y=3.45e^{-3.45x}+1.06e^{-1.24x}$ with $R^2=0.873$. For further investigation, the average $K(i)$ of all k-degrees was obtained as follows. Where N_k represents the number of vertices with degree k.

$$K(\bar{k}) = \frac{1}{N_k} \sum_{v_j \in V} K_{(i)} \tag{12}$$

As seen in Figure 8, the $c$for the IAN network equals $y=3.45e^{-3.34x}+1.06e^{-1.24x}$, with $R^2=0.987$ which is far more accurate than the value obtained for $K(i)$. According to Figure 8, there is a correlation among the degrees, so that nodes with lower degrees are connected to nodes with higher degrees, for example, all the nodes with degree 1 are only connected to the Mehrabad node with degree 64, confirming the network is disassortative. According to the results obtained here, the IAN network is correlated, so that as the k increases, the correlation decreases, and as the k decreases, the correlation increases. For instance, Mehrabad airport with the highest degree has the lowest value of $K(\bar{k})=7.64$.

4.4. Correlation between the clustering coefficient and degree

Clustering degree correlation measures the clustering coefficient of a node about the degree of that node. The average clustering coefficient of all nodes with degree k is obtained through the following equation. Where N_k is the number of nodes with degree k.

$$C(k) = \frac{1}{N_k} \sum_{v_j \in V,\ k_i = k} C_i \tag{13}$$

Figure 9 shows the graph for the Clustering Degree Correlation. The relationship between $C(k)$ and the degree is equal to $y=0.478e^{0.01x}$ with the value of $R^2=0.991$, indicating that in the IAN network the clustering coefficient has an accurate relationship with the degree. In this equation as the

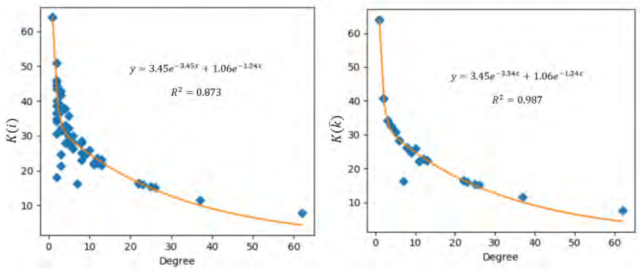

Figure. 8. Degree correlation

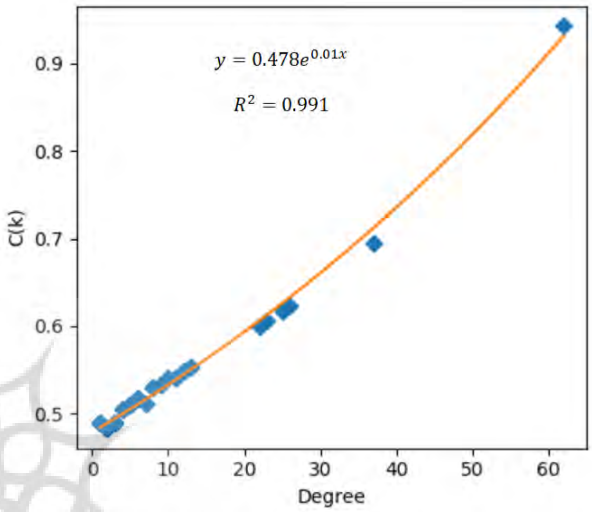

Figure. 9. Correlation between the clustering coefficient and degree

degree increases, the clustering coefficient enhances as well. For example, Mehrabad Airport with the highest degree has the highest clustering coefficient and those airports with a degree of one, have the lowest clustering coefficient. Increasing the clustering coefficient with an increase in degree shows that larger airports are interconnected; in fact, larger airports tend to be enclosed by airports with larger degrees. This coherence of behavior at the airports of IAN indicates that there is a higher volume of commute in larger airports and more transport takes place between the larger airports. Airports with lower degrees have lower clustering coefficients, suggesting that these airports are either not enclosed at all or are enclosed by lower-degree cities.

4.5. Correlations between Centralities and Passenger volume

In this section, the relationship between the total number of passengers traveling from each airport for a year and degree, betweenness, and closeness centralities is studied. The correlations are shown in Figure 10, according to the figure and the values obtained for R^2, the volume of passengers is more associated with the number of flight paths in each airport, which means that increasing the number of flight paths of each airport, or, in other words, by increasing the degree number per airport, a larger number of passengers will be transported in that airport. For example, Mehrabad Airport with 62 flight-outs carries more than 8 million passengers a year. After correlating the degree to the volume of passengers, the

Table 4. Top 15 Cities based on degree, closeness, and betweenness.

Rank	***Degree(C_D)***	***Closeness(C_C)***	***Betweenness(C_B)***
1	MehrAbad	MehrAbad	MehrAbad
2	Mashhad	Mashhad	Mashhad
3	Shiraz	Shiraz	BandarAbbas
4	Esfahan	Esfahan	Shiraz
5	BandarAbbas	BandarAbbas	Esfahan
6	Kish	Kish	Kish
7	Ahwaz	Ahwaz	Ahwaz
8	Kerman	Kerman	Siri
9	Rasht	Rasht	Kerman
10	Qeshm	Qeshm	Zahedan
11	Khalij-Fars	Khalij-Fars	Bushehr
12	Tabriz	Tabriz	Rasht
13	Zahedan	Zahedan	Qeshm
14	Bushehr	Bushehr	Khalij-Fars
15	KermanShah	KermanShah	Tabriz

Table 5. Correlation between centralities.

Centralities	***Degree***	***Betweenness***	***Closeness***
Degree	1	0.916917833	0.985713944
Betweenness		1	0.970796293
Closeness			1

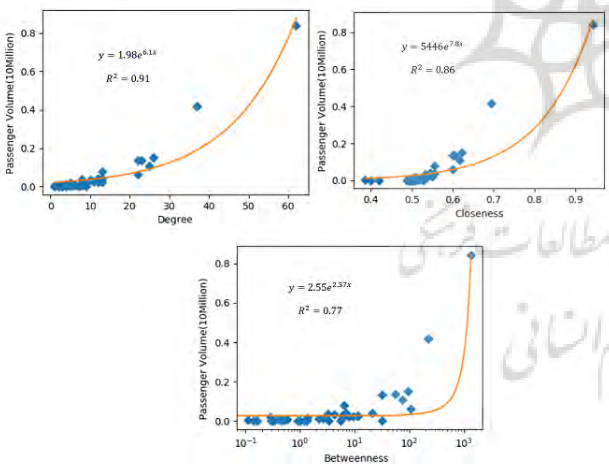

Figure. 10. The relationship between the number of annual air passengers with centralities

closeness index shows more relevance with the number of passengers than betweenness.

5. Discussions

In this paper, the structure of IAN was examined from the perspective of complex networks. IAN is a complex network, with its nodes being the airports and its edges being the direct flights between the airports. The IAN structure has the characteristics of small-world networks that are similar to those of Australia, China, the United States, India, and Italy. Its degree distribution follows the power law with high accuracy, supporting the presence of a small number of airports with a large number of paths such as Tehran and Mashhad. IAN is a disassortative network, like Australia, China, and the United States. In the IAN network, the hubs are enclosed by lower-degree nodes. The following cases can be of great importance to be analyzed by policymakers and airline service providers.

IAN is an SW network. The average shortest path length is equal to 1.9, emphasizing that, on average, two flights are needed to go from each city to another. In some limited cases, three flights are required for movement.

The IAN is a disassortative network, meaning that the majority of smaller airports are connected to larger airports and the connecting routes from the smaller cities to the larger cities are well provided.

The correlation graph between the degree and clustering coefficient in the IAN exhibits a clear pattern; as such, the more paths an airport has, the higher the clustering coefficient it will have. This means that large airports, apart from being connected to smaller airports, which was understood from the disassortative nature of the network, are also connected to national hubs.

Analysis of centrality relations indicated that the airport with the highest degree has the highest betweenness as well as the highest closeness. For example, Mehrabad Airport of Tehran and Mashhad Airport is ranked first and second, respectively, in all the tree centrality graphs.

6. Conclusion

In the current research, it is also attempted to identify the Iranian airport structure and obtain the quality of connections across the regions and airports, and also to identify the airports that play an important role in the core structure of Iran's airline. This manuscript is the first article to analyze Iranian airports with a complex network approach. Research on airport networks has been carried out in some other countries and these researches have been compared with our research.

As other countries have done this research and surveyed their airport networks, we have also done this research for our country Iran. This research can help to expand airports and also identify important airports in the country.

Declarations

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Authors' contributions

BA: Study design, acquisition of data, interpretation of the results, drafting the manuscript; statistical analysis, revision of the manuscript; KRF: Study design, interpretation of the results, drafting the manuscript; AJB: Study design, interpretation of the results, drafting the manuscript, supervision;

Conflict of interest

The authors declare that there is no conflict of interest.

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