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Statistical and Reliability Analysis of the Iran Railway System as a Complex Network

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ABSTRACT

The transportation networks analysis aims to investigate the system's structural characteristics and dynamical evolution to evaluate the transit services. In this regard, the topological characteristics of the Iran railway network have been studied and compared to two well-studied railway networks, China and Spain. Also, the network vulnerability to station failures has been studied based on different attacks. Accordingly, in the first step of this work, the city stations have been extracted from Iran railway information to construct the network. Then, some structural properties, including the degree distribution, betweenness centrality, clustering coefficient, and distance distribution, have been analyzed for three networks. Finally, the network reliability has been evaluated using a random as well as adversarial attack. The structural analysis reveals that the Iran railway network would require some structural optimization to improve the economic benefits. Based on the vulnerability investigation, the network efficiency of the network will be dropped more quickly utilizing the maximum betweenness attack. In addition, as it were, little parts of the network seem to keep their usefulness as the estimate of the giant component is diminished exceptionally strongly when less than 20% of nodes are expelled from the network haphazardly or intentioned.

Keywords: ***Transportation Systems; Railway Network, Complex Network Analysis, Vulnerability Assessment.***

1. Introduction

The theory of complex networks (CNs) has been widely applied on different applications such as power grid [1], cryptocurrency [2], Internet of Things [3], swam intelligence [4], text processing [5], accounting cloud services [6], human action recognition [7], Electroencephalogram signals [8], data mining [9], predicting brain age [10], features extraction of MRI images [11], detecting delay propagation in regional air transport systems [12], etc.

Any transportation system can be modeled as a complex network. Afterwards, such a mathematical model could be employed in order to investigate the structural and vulnerability characteristics of the system using degree-based features, path-based features, and community-based features [13], [14], and [15].

One the most critical transportation systems is the Railway networks that have been studied in CN-based research works [16]-[23]. Chinese railway network (CRN) [16], [18], China high-speed railway network (CHSRN) [17], [20], [21], urban rail transit (URT) [19], China Railway Express (CR express) [22], and railway incident of Japan [23] are some of the railway networks studied through complex network concepts.

Today, Spain, Germany, China, Japan, South Korea and France use high-speed Railway (HSR). France opened the first high-speed railway from Paris to Lyon in 1981, followed by Spain, Germany and other countries. In 2020, China built the longest and the most complex high-speed railway network in the world. Also Spain's high-speed railway began in 1992 and now has a network of about 3,400 km. The Spanish transport network has been the subject of much historical debate because the transport infrastructure has greatly influenced Spain's social organization and economic development. Most of the research of the Spanish transport network dates back to the post-1850 period [24], [25], [26]. By 2007, Spanish railway stations were connected, and to this day the number of railways and stations is increasing [27].

The Iran railway network has been studied in some of the recently published works [28], [29]. However, the structural and robustness of the network using the CN analysis have not been evaluated, yet. Thus, the aim of this paper is to investigate structural and vulnerability characteristics of the Iran railway network which is an extended version of our previous published work [30].

Particularly, we have extracted the degree distribution, betweenness centrality, distance distribution, and network efficiency to discuss about the network structure and assess two types of attacks in order to evaluate the network robustness [31]. According to the experimental results, it appears that the network's average degree and the average shortest paths are about 2, 40, respectively. This observation shows that several stations within the railway network are available in a moderately costly and time-consuming way. In addition, depending on the attacks performed on the node, the overall efficiency of the network will drop faster using intentional attacks. Also, if less than 20% of the nodes are accidentally or intentionally removed from the network, the estimates of the giant component will drop rapidly, allowing a small part of the network to maintain its usefulness.

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The remainder of this paper is structured as follows: In Section 2, the network construction is described. Section 3 discusses about the topological properties of the Iran railway network. The network reliability is analyzed in Section 4. Finally, the last section is our conclusion.

2. Data And Network Construction

The Iran 2020 railway plan is used to construct the network. The constructed network is composed of 437 nodes (cities) and 565 edges (rail lines). Thus, representing the railway system as $G=<V,E>$, we would have $|V|=437$ and $|E|=565$.The network topology of the Iran railway network has been shown in Figure 1.

As shown in Figure 1, each railway station is considered as a node associated with other nodes through rail lines. Also, as the network characteristics of the Iran railway network will be compared to other well-studied networks, two railway networks of Spain and China have been taken into account. According to the China Railway Map, the topology of China includes 393 nodes and 558 edges. In addition, Spain has 135 nodes and 173 edges, which are shown in Figures 2 and 3, respectively. Figure 2 shows that China has the highest rail lines compared to the Iranian and Spanish railways.

3. Structural Analysis

3.1 Degree Distribution

The degree of a node is calculated as Eq. (1).

$$k_i = \sum_{j}^{N} x_{ij} \tag{1}$$

where $x_{ij}=1$ when two nodes i and j have a link and it is 0 in otherwise. The node degree is the simplest network measure to reflect the node significance. That is, the bigger the node degree implies higher the importance. For instance, Tehran, Ahvaz, and Ardakan are among the stations with more railway lines into the surrounding regions compared to the stations of Isfahan and Orumiyeh.

In order to obtain the degree distribution, the probability distribution is calculated as Eq. (2).

$$P_{\deg}(k) = \frac{\alpha}{N} \tag{2}$$

where α is the number of k-degree nodes.

The degree distribution of Iran's railway network has been shown in Figure 4 and Figure 5 (in log-log scale). As shown, we have $P(k=2)=0.8$. This observation indicates that about 80% of the railway stations are restricted to the previous and the next stations. For illustration, the Shahroud station encompasses a railway line to Kalatkhan and Bastam stations. In addition, about 10% are 1-degree as they are the starting or finishing nodes. This is while, less than 10% of the stations show higher connectivity and are connected to three other stations, mainly found at the center region. Furthermore, some stations have more than three associations with others cities. In comparison to the Chinese high-speed railway network, it could be seen that the maximum degrees in the both networks are the same. On the other hand, it is shown that each city station is mote likely connected to at most two

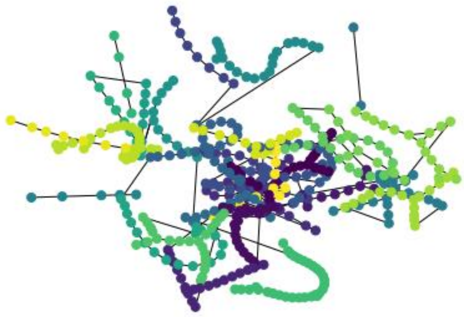

Figure. 1. The constructed network of Iran railway including 437 city stations with 565 of rail lines.

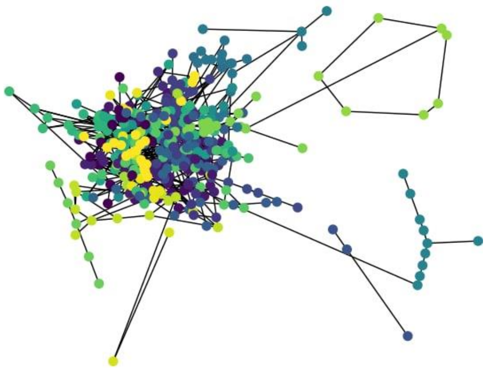

Figure. 2. The China railway network with 425 city stations and 673 rail lines.

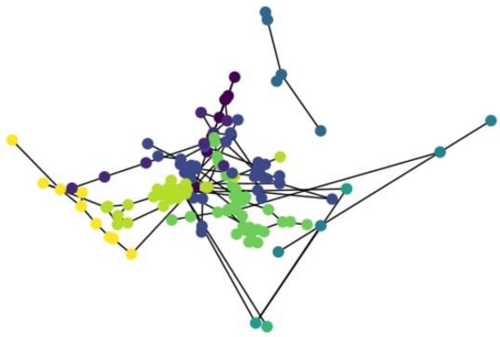

Figure. 3. The Spain railway network of 135 city stations with 173 rail lines. As the network is under construction, the stations have been shown in two connected components.

other stations [31]. As shown in Figure 4, in the Spain network, most nodes have a degree of 2 such that $P(k=2)=0.34$, but the probability for Iran is higher than Spain. In other words, there are more railway stations in Iran than in Spain, which are connected to only two railway stations around them. Also, in China Railway, due to the presence of numerous railway lines between stations, unlike the railway of Iran and Spain, most of the railway stations in this nation are associated with the three stations around them.

According to the comparisons made between the railway stations of the three countries in Figure 4, it has been determined that there are stations with the exact probabilities in the Spanish and Iranian railways, the degrees of which are 5. In addition, in China and Spain, there are nodes with the exact probabilities that have degrees 6 and 7. In addition, there are some stations on the Chinese railway that are connected to 8 other stations, while for the Spain and Iran networks, the maximum degree is 7 and 6, respectively.

3.2 Cumulative degree distribution

The cumulative degree distribution captures the probability of randomly selecting a node with degree not less than k in a given network, and is written as Eq. (3):

$$P(k) = \sum_{k'=k}^{\infty} p(k') \tag{3}$$

As a critical property, the cumulative degree distribution can determine many network phenomena of real transportation systems, from network robustness to the spread of traffic flow [32].

As can be seen in Figure 6, initially, the probability of random selection of a node with grade 2 or less in the Iranian railway network is higher than other networks because most nodes in the Iranian railway network are only nodes with degree two, but with increasing degrees of nodes (more than 3), the probability of random node selection in China and Spain networks is higher than the Iranian railway network. This is because the number of stations connected to more than two stations on the Chinese and Spanish railways is higher than the Iranian network. Therefore, they are most likely selected randomly.

Referring to the Iran railway map, a number of railway stations with their associated degrees have been reported in Table 1. In is observed that most of the cities are linked with the other two cities and thus have degree 2.

3.3 Betweenness Centrality

The betweenness centrality (BC) determines the significance of the nodes through calculating the shortest path across a given network node. Let $\sigma_{st}(i)$ be the number of shortest paths between the nodes *s* and *t* that pass through the node *i*. Then, the BC measure is characterized as Eq. (4):

$$B_i = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{4}$$

where σ_{st} represents the total number of shortest paths between the two nodes *s* and *t*. The higher the betweenness value between the nodes, the higher the path-based centrality of that nodes. A disruption of the network from such a point thus causes a high degree of structural disruption. Figure 7 depicts the betweenness distribution of the network. From this, we can infer that there is a strong relationship between the degree distribution and the betweenness distribution.

The betweenness distributions of the two other networks have been depicted in Figure 8 (China) and Figure 9 (Spain). The comparison shows high similarity of three networks.

3.4 Clustering Coefficient

The value of clustering coefficient (CC) shows which nodes in a graph tend to compose a cluster together and is defined as Eq. (5):

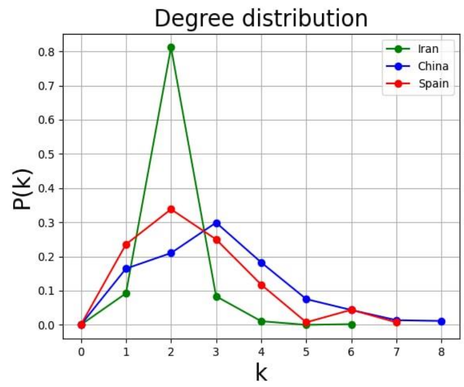

Figure. 4. Degree distribution of the Iran railway network in comparison with China and Spain networks.

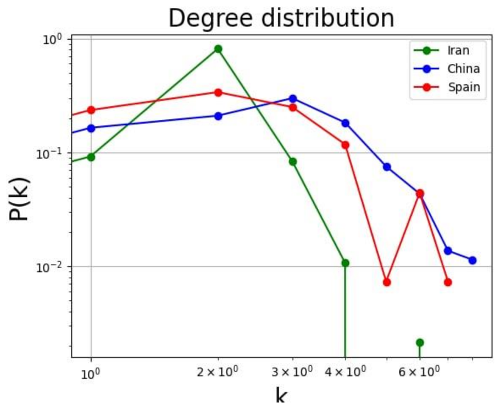

Figure. 5. Degree distribution of the Iran railway networks in comparison with the China and Spain networks (log-log scale).

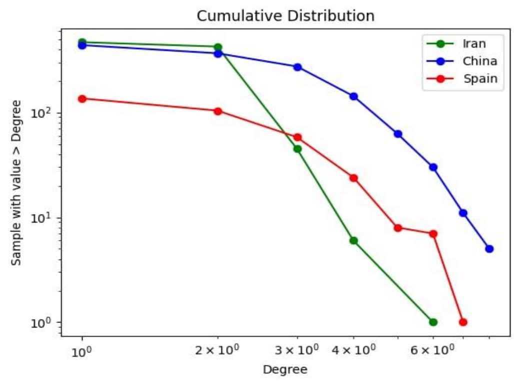

Figure. 6. The Cumulative degree distribution of the three networks.

Table 1. The degree of a few city stations in Iran railway network

Station	***# links***	***Station***	***# links***
TEH	3	ESF	2
SEM	2	KRMS	1
GIL	2	AHV	3
KAR	2	SHR	1
MAD	1	KASN	2
KARJ	3	SAV	2
GARM	3	ZNJ	2
TABS	2	KRM	2
SABZ	2	RST	1
NSB	2	TBZ	2

$$C_i = \frac{2e_i}{k_i(k_i - 1)} \quad (5)$$

in which e_i is the number of links between the neighbors of the nodes *i*. As the maximum value of e_i would be $k_i(k_i - 1)$, the CC value of each node falls within [0,1]. The CC value of the whole network is characterized as the average of the CC values of all the nodes within the network.

The CC values of the nodes are shown in Figure 10 which indicates that the CC value for most of the network nodes is zero. This achievement is accordance to the degree distribution of the networks where most of the nodes are 1 or 2 degree nodes (see for example the Orumiyeh station which is a 1-degree node and CC value of 0). However, the CC value of about 0.3 and even near to 1.0 is observed for a few stations drawn in Figure 10.

The CC values of the nodes of the China and Spain networks have also been shown in Figures 11 and 12. It could be revealed that the two network China and Spain have much higher connectivity between their respective stations than the Iran railway network. In the China network, several nodes have the CC value of about 0.4 and the CC of four nodes are 1.0. This result supports the degree distribution of the China network shown in Figure 4 (see for example, the Suide station as a 4-degree node with a CC value of 0.4). The overall CC value of the China network is about 0.09 while this quantity for the Spain network is about 0.08. In average, the CC value of China and Spain networks are almost 10

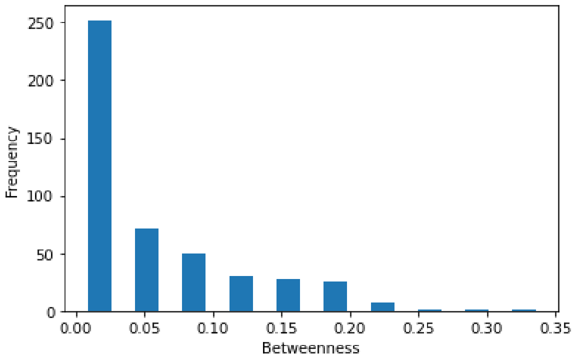

Figure. 7. The betweenness distribution of the Iran railway network

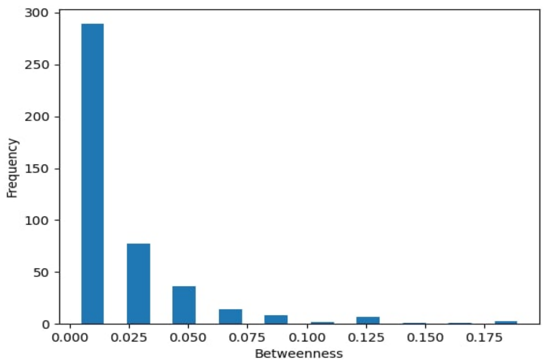

Figure. 8. The betweenness distribution of the China railway network

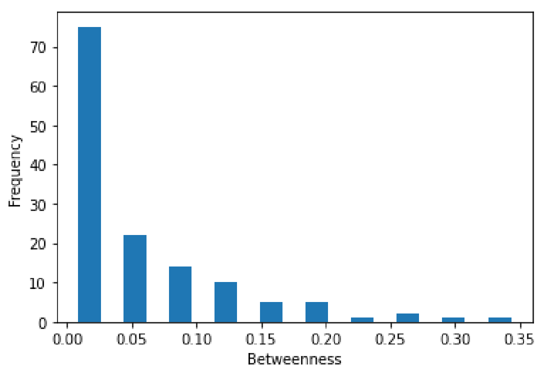

Figure. 9. The betweenness distribution of the Spain railway network

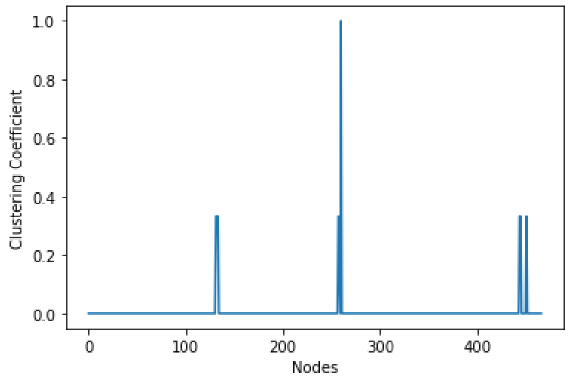

Figure. 10. The CC of the all nodes of Iran railway network. The average CC value is 0.007.

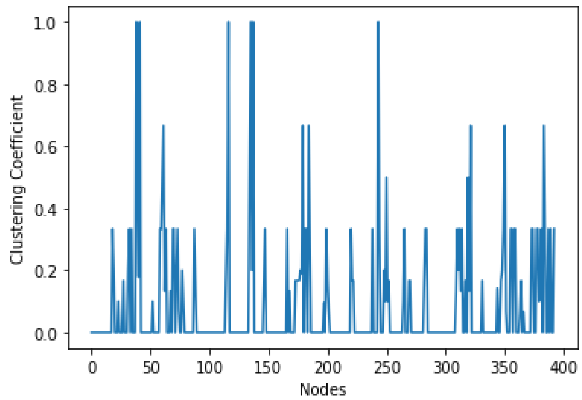

Figure. 11. The CC of the all nodes of China network. The average network CC is 0.09.

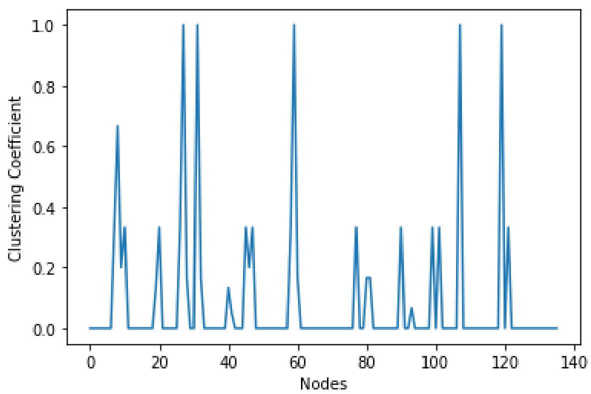

Figure. 12. The CC of the all nodes of Spain network. The average network CC is 0.08.

times larger than the Iran railway network which defines the better system functionality in terms of the network connectivity.

3.5 Distance distribution

Distance distribution is another useful network measure that is similar to the betweenness measurement. The distance of a given node pair is defined as the shortest path length between them. By calculating the distances of the all node pairs as d_{ij}, the average nodes distance of the whole network is defined as Eq. (6):

$$L = \frac{2}{N(N-1)} \sum_{i,j} d_{ij} \qquad (6)$$

As much as the value of L is smaller, the railway stations would have higher connectivity. The distance distribution of the Iran railway is shown in Figure 13 where we have L about 10. For instance, the path length of Tehran-Qom is about 9 where the occurrence probability of such a path length has been shown about 0.1 in Figure 13.

The similar analysis has been performed for the China and Spain networks as shown in Figure 14 and Figure 15. As in the China and Spain networks, the stations are more likely to compose several communities, the distance distributions of the nodes in these two networks show more diversities. See the Beijing-Benhong path in the China network and the SanSebastian-Burgos path in the Spain network as two examples. In the first one, the shortest path length is about 3 with the path probability of 0.07. In the second example, the distance is about 2 with probability of 0.08.

Also because the map of Spain railway is unconnected so another shortest path length has calculated for four stations in Figure 16. As appeared in Figure 16, there are 4 nodes in this network that are associated to each other with no shortest path.

4. Vulnarability Analysis

In this section, the vulnerability of the railway network is analyzed against the station failures. To simulate the station failures, three types of the nodes attacks have been taken into account. In first type, a portion of the network nodes is removed randomly while in the second and the third attacks, the nodes with the maximum degree and the betweenness centrality are selected to be removed, respectively. In order to evaluate the status of the network after each attack, the global network efficiency is employed as defined as Eq. (7):

$$E = \frac{2}{N(N-1)} \sum_{i,j} \frac{1}{d_{ij}} \qquad (7)$$

Moreover, the size of the giant component will be used as well.

The size of the giant component after each network attack has been measured and depicted in Figures 17, 18, and 19 for the three networks, respectively. It should be noted that, because of the low network connectivity in the Iran railway, the results of the two intentional attacks, i.e. the maximum degree or betweenness attacks, might not be different with each other.

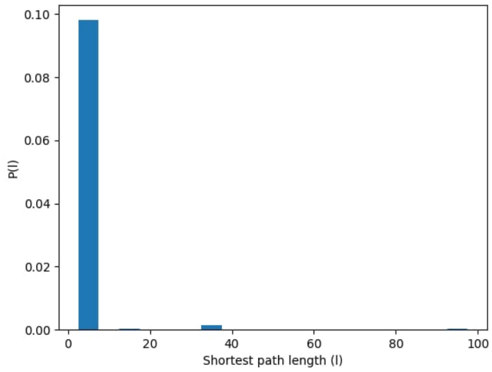

Figure. 13. The shortest path length distribution of Iran railway network

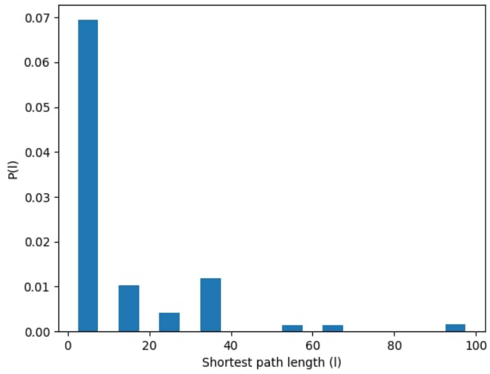

Figure. 14. The shortest path length distribution of China's railway

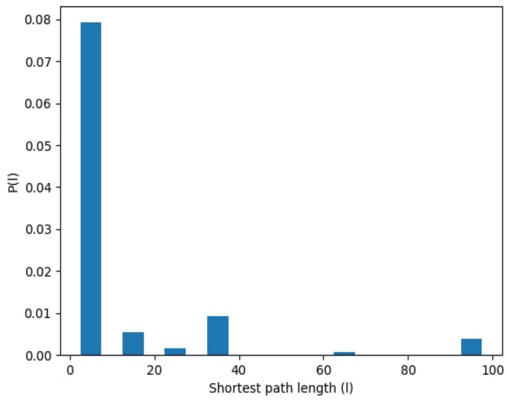

Figure. 15. The shortest path length distribution of the Spain's railway

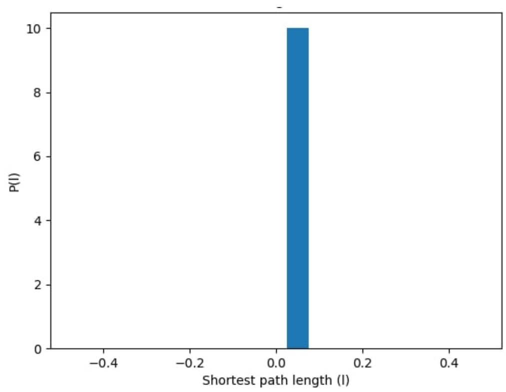

Figure. 16. The shortest path length distribution of unconnected component of the Spain's railway

As shown in Figure 17, the largest component of the Iran railway would be about 35 nodes after the removing the 20% of the nodes randomly or with the maximum-degree attack. The railway network will not be exist anymore when 90% of the nodes are removed with any nodes attacks. However, as it is shown in the figure, the two intentional attacks could bring the highest reduction in the size of the giant component from the initial state till the 20% nodes removal.

The two intentional maximum degree/betweenness attacks do, also, the most damages to the China network [21]. The giant component analysis of the China network after the three attacks is shown in Figure 18. According to this figure, the China network shows a higher robustness to the station failures as the reduction slope is much smaller than the Iran railway network. While the network almost does not exist as a transportation system in the Iran case with 20% nodes removal, in the China network, this status is achieved after 40% of the nodes removal.

Imprecisely, it could be say that the robustness of the China railway system is about 2 times higher than the Iran railway.

The Spain network reliability behaves as a moderate transportation system as the largest component in this network loses its size faster than the China and slower than the Iran railway networks. The vulnerability status of the Spain railway network is shown in Figure 19 based on the size of the giant component.

According to the results of these three networks, if only a small part of the nodes in the network are attacked, the Iran railway network is damaged more. In contrast, in these situations, the maximum betweenness attacks on the Spanish network can result in the strongest hits on the network. In addition, if 30% of the nodes in the system are deleted, a random attack on Iran's rail network will do the most damage to the network. However, the China and Span networks will be damaged hardly by the betweenness attack. What all three networks have in common is that if more than 60% of the network nodes in Iran, Spain and China are removed, they will be vulnerable to random attacks on the network.

However, using the global network efficiency, as a measure of the network reliability, makes the destructive effects of the three attack types, more apparent. Properly, using the maximum betweenness attack makes the network more vulnerable. The process of deleting a node with global efficiency is as follows:

Step 1: calculate the values of node measures of the network.

Step 2: sort the values from the expansive to the small for each node measure.

Step 3: delete the nodes agreeing on the sorted values of one node degree at each step.

Step 4: evaluate the network performance by degree measure when a node is deleted from the network.

Step 5: repeat step1 to step 4 for each node in the network.

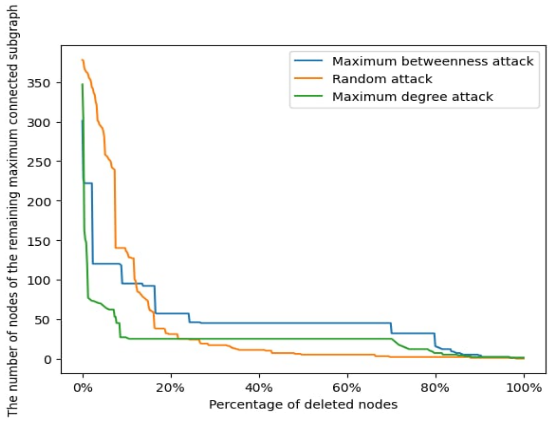

Figure. 17. The measure of the giant component amid the three-node removal assaults of Iran’s railway.

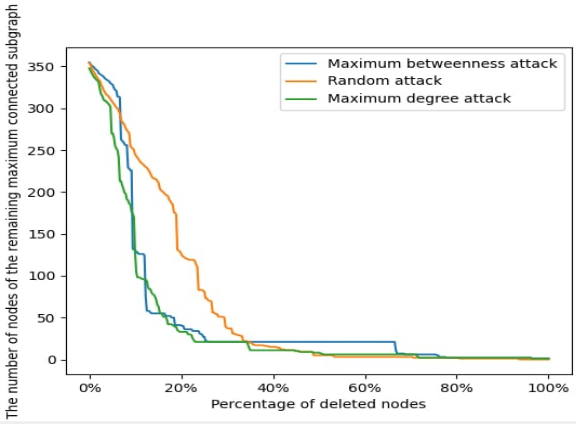

Figure. 18. The measure of the giant component amid the three-node removal assaults of China’s railway.

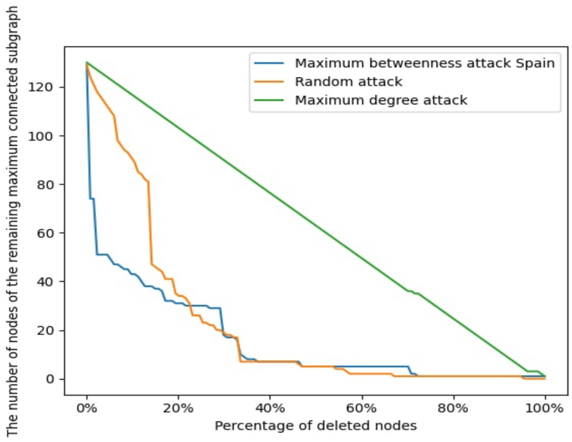

Figure. 19. The measure of the giant component amid the three-node removal assaults of Spain’s railway.

Figure 20 shows that the value of the random attack efficiency has dropped significantly (from 0.035 to less than 0.01). According to this figure, the network efficiency is maximized when no attacks are occurring. The fastest reduction of the network efficiency is obtained after about 10% of the nodes removal. After that, the random attack could make a more damage on the network in comparisons with the intentional attacks for the Iran railway network. If 80% of the nodes are attacked, the network efficiency will be lower than the maximum betweenness or degree attacks. In addition, if more than 90% of the nodes are removed, the network efficiency will be minimized according to the three attacks.

Based on the network efficiency, a random attack on the China high-speed railway would not have a significant impact on the global efficiency of the network. On the other hand, within the Iran's rail network, the network efficiency is significantly reduced in the event of a random attack [21]. Figure 21 shows a sharp drop in the value of global efficiency when using random attacks on a Chinese network. Apparently, the efficiency of the network is steadily declining from 0.12 to less than 0.04.

According to Figure 21, initially, the network efficiency of the China network is maximized. The network efficiency will be reduced to 0.04 after removing just 10% of the nodes. Therefore, in case of the random nodes removal, the network efficiency would be larger than that of the maximum degree/betweenness attacks. This situation remains unchanged when the amount of the nodes under attacks increases up to 90% of the network nodes.

An extremely sharp decrease of the network efficiency is observable using the maximum betweenness attack in Spain network, as shown in Figure 22, where the network efficiency drops from 0.16 to lower than 0.08. More precisely, after removing 20% of the nodes according to the maximum betweenness, the network efficiency comes to the less than 0.06. So, in case of using the maximum-degree attack, the global efficiency will be more than the maximum-betweenness or random attacks. In the event that about 30% of the nodes are removed, the network efficiency by maximum-betweenness attack or the maximum-degree attack will be the same. Moreover, by removing more than 90% of the nodes, the network efficiency will be at its lowest level using the maximum betweenness and the random attacks while the maximum degree attack does not impact on the network efficiency of the Spain railway system.

In overall, it has been observed that the network efficiency may be influenced by all the three network attacks. In the Iran railway, most of the network functionality is lost after removing only 10-20% of the nodes even randomly. This is while, for the other two railway networks, this situation is happened by removing about 40% of the nodes which indicates better network robustness. These results confirm the previous structural analysis of the three networks discussed in Section 3.

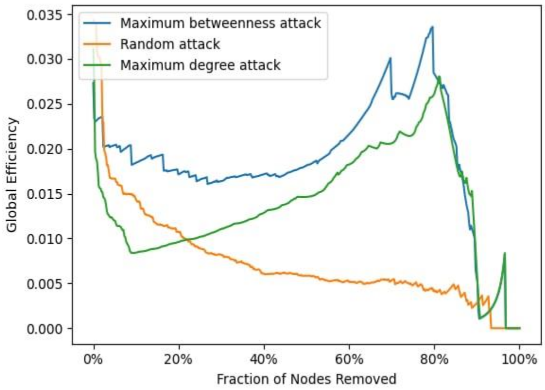

Figure. 20. The changes within the global efficiency under three attacks of Iran's railway.

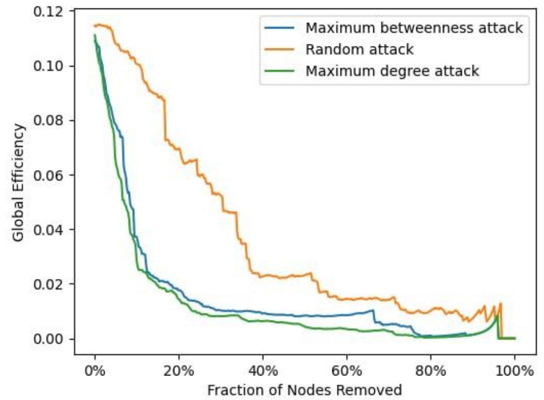

Figure. 21. The changes within the global efficiency under three attacks of China's railway.

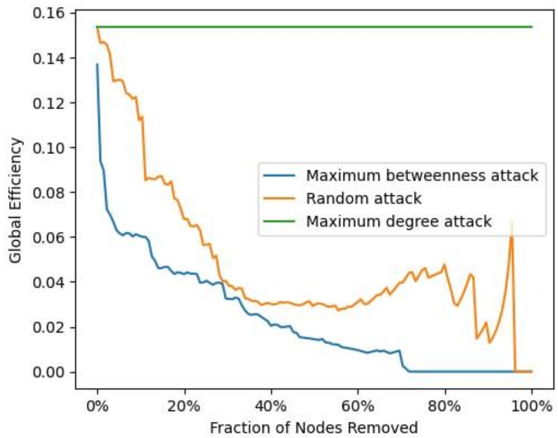

Figure. 22. The changes within the global efficiency under three attacks of Spain's railway.

5. Conclusions And Future Work

The degree, betweenness, and distance distributions of the Iran railway network indicate that most of the stations participate in a ring topology. Specifically, the average degree, path length, and clustering coefficient are respectively 2.02, 10, and 0.007. These values, compared to the China and Spain networks, makes the Iran transportation network more costly for both travelling and maintenance.

In order to evaluate the vulnerability of the Iran railway, the node removal attack has been employed to quantify the amount of the network robustness in terms of the giant component and the network efficiency. In this way, a portion of the nodes is selected randomly or intentionally. In the latter case, the candidate nodes are removed according to its degree or betweenness values. In all the three attacks, the Iran railway system shows more potential vulnerability to the failure of the stations compared to the China and Spain networks. Based on the analysis, it can be concluded that due to the existence of a fewer railway lines between the two stations, the Iran railway is more vulnerable to random attacks than the China and Spain networks. In addition, due to a large number of central nodes in China railway, the maximum degree attack causes the most damage to the network, while this attack on the Spain and the Iran networks has less network impact. Regarding the efficiency of the network, it can be said that by removing a large percentage of the nodes using a random attack, the performance of the Iran network is greatly reduced, while this attack has less impact on the networks of Spain and China.

In overall, although the Iran railway system is under the development, both the structural and vulnerability analysis of the system in comparison with the two famous railway network indicate that the network connectivity should be optimized even further. However, it should be noticed that the station failures in the any railway network could be handled by the other transportation systems such as the inter-city taxi or the airlines to keep the functionality of the whole transportation system. As a future work, the simultaneous analysis a multi-layer transportation system could be performed for the Iran case study.

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Authors' contributions

MM: Study design, acquisition of data, interpretation of the results, statistical analysis, drafting the manuscript; HS: Study design, interpretation of the results, drafting the manuscript, revision of the manuscript; RA: Supervision, drafting the manuscript.

Conflict of interest

The authors declare that there is no conflict of interest.

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