Assessment of Node Importance in Air Transportation Networks using Multi-Criteria Decision Analysis

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Complex network theory provides powerful tools to analyze and understand the structures and dynamics of complex air transportation systems. One example for a successful application of complex network theory in air transportation systems are airport networks, where airports are nodes, and two airports are connected if there exist flight connections. In complex networks, a node can be characterized by several centrality metrics: Degree, betweenness, closeness, eigenvector, etc. How to identify which node is most important or most critical, regarding different notions of centrality, is a typical multi-criteria decision problem. This paper incorporates Multiple Criteria Decision Analysis (MCDA) techniques to assess node importance in air transportation networks. First, we investigate the correlation among a large set of metrics in order to identify independent, representative metrics. Second, we derive preferences among multiple metrics using Entropy method. Third, we apply an improved MCDA method which can maintain the ranking consistency of the alternatives. In the end, we perform uncertainty assessment for preferences among multiple metrics. Our proposed methodology is applied to an airline network.

I. Introduction

Large-scale complex socio-technical systems, such as air transportation and power grid, can be represented as complex networks, where elements of complex systems are regarded as nodes; and there is a link between two elements if they interact with each other. The definition of the most important (critical/vital/key) nodes is different with the most influential nodes. While there is no unique definition for the most important nodes; the most influential nodes are more relevant for information and epidemic spreading in social and biological networks.

In general, there are two approaches to assess the node importance of complex networks: a detection approach and a destruction approach. The detection approach concentrates on comparing several statistical metrics,[3] the importance of a node is equivalent to the significance generated by the connection between this node with other nodes. In the destruction approach, the importance of a node is measured by the extent of damage in the network connectivity when the node is deleted. Both approaches have their advantages and disadvantages: The detection approach suffers from nonuniqueness[3] because there exits a large set of metrics and different metrics may provide different, even conflicting results; while the destruction approach needs higher computational costs. This paper extends the detection approach by incorporating Multiple Criteria Decision Analysis (MCDA) techniques in the assessment of node importance in complex networks.

This paper is organized as follows. Section II introduces the background. Section III presents our methodology to assess node importance by incorporating MCDA techniques in complex networks. Finally, conclusions are drawn in Section IV.

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II. Background

This section provides literature review of MCDA in complex networks. Reggiani et. al. analyzed the topological properties of Lufthansa airline network and used multi-criteria analysis to four alternative networks in terms of three macro-criteria: network concentration, topology, and connectivity.[25] The authors carried out five scenarios by considering: all the three macro-criteria simultaneously, each macro-criterion separately, and concentration and topology together. However, in each scenario, an equal weighting factor has been given to the single criterion. Yu et. al. used a multi-attribute decision making method (TOPSIS) to identify key nodes in complex networks.[33] Three network examples: Krackhardt kite network, American advanced research project agency network, and a scientific cooperation network, were used to demonstrate the effectiveness of the proposed approach.

Wei et. al. proposed a new centrality measure to identify the influential nodes in complex networks based on the Dempster-Shafer evidence theory.[31] Gao et. al. proposed a new evidential semi-local centrality to identify the influential nodes in complex networks.[14] Gao et. al. extended this work and proposed a local structural centrality measure which consider both the number and the topological connections of the neighbors of a node.[15] Du et. al. proposed a new method to identify influential nodes in complex networks based on TOPSIS,[10] the Susceptible-Infected model was used to examine the spreading influence of the nodes identified by the proposed method. Chen et. al. proposed a local ranking algorithm which takes into account the number of neighbors, the neighbors influences, and the clustering coefficient.[6] Rocco-S and Ruiz suggested to use global sensitivity analysis methods to assess the component importance in a network,[26] where the importance of a component is defined as the contribution of a component to a specific measure of the network performance. The authors showed that different approaches could generate different rankings of importance and they suggested combining the information in order to generate a composite indicator. One solution is to apply Multiple Criteria Decision Analysis (MCDA) techniques. Zhang et. al. used fuzzy Analytic Hierarchy Process (AHP) and TOPSIS to assess the node importance of complex networks in product research and development team.[34] Shetty and Adibi identified the most important nodes in social networks based on graph entropy, with the evaluation on the Enron email dataset.[28] They interpreted the important nodes are those who have the most effect of the graph entropy when they are removed from the graph.

Furthermore, Jamakovic et. al. studied the relationships between topological metrics in real-world networks and showed that some topological metrics tend to be more correlated than the others, with the implication that there is redundancy between topological metrics.[18] Li et. al. investigated the linear correlation coefficients between widely used network metrics in three network models and in functional brain networks.[20] Bounova and de Weck presented an overview of topology metrics and their relationships for various ensembles of synthetic and real networks.[3] The authors cautioned against studying a single measure or pulling networks from different domains and topologies together. Onnela et. al. introduced a framework for constructing taxonomies of networks based on community structure.[24] Garcia-Robledo et. al. presented an experimental study on the correlation between commonly used network metrics on the topology of the Internet.[16]

However, there are several limitations in previous work.

1) The correlation among the criteria is not considered. When we use MCDA method, the evaluation criteria should be kept as independent as possible. Thus, it is necessary to examine the correlation among multiple evaluation criteria in the criteria identification step. For instance, if two criteria have high correlation with each other, then they should be merged into one criterion or one of them should be used in the further evaluation step.

2) Equal weighting factors have often been used to network metrics, preference information has not been considered. As one way to represent a decision maker's attitude in favor of one criterion over another when choosing between alternatives, weighting factors are often highly subjective, considering that they are elicited based on the decision maker's experience or intuition.[2,12] The inherent uncertainty associated with the weighting factors has significant impacts on the final decision solution.

3) TOPSIS method suffers from ranking inconsistency problem. When an alternative is removed from or added to the candidate alternatives, the ideal solutions will probably change and the Euclidean distances to the ideal solutions will also change. Thus, the top-ranked alternative may become inconsistent when the candidate alternatives are changed. It has been pointed out that the cause of rank inconsistency with TOPSIS lies in the calculation step of determining the two hypothetical ideal solutions.[8]

III. Our methodology

In this paper, we propose a new methodology to assess node importance in complex networks by incorporating MCDA techniques. In the first step, we investigate the correlation among a large set of metrics in order to identify independent metrics. Secondly, we derive preferences among multiple metrics using Entropy method. Thirdly, we apply an improved MCDA method which can maintain the ranking consistency. In the end, we perform uncertainty assessment for preferences among multiple metrics.

An airline network (data available at `https://gephi.org/datasets/airlines-sample.gexf`)[10] is used as a running example to explain each step of our proposed methodology. In the airline network, there are 235 nodes (airports) and 1297 links (flight connections), with an average degree of 11 and a maximum degree of 130.

III.A. Correlation analysis for the multiple metrics

We investigate the correlation among the network metrics in the criteria identification step. We analyze fourteen network metrics in order to identify the most important nodes. These metrics are listed as follows.

1. **Degree:** $D_i = \sum_j a_{ij}$, where a_{ij} is the connection between node i and node j: $a_{ij} = 1$ when there is a connection existing; $a_{ij} = 0$ otherwise. For all pairs of nodes in the network, a_{ij} composes the adjacency matrix. Degree refers to the number of connections with other nodes.

2. **Average neighbor degree:** The average degree of the neighborhood of each node.

3. **Betweenness centrality:** $B_i = \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$, where σ_{st} is the number of shortest paths going from node s to node t; $\sigma_{st}(i)$ is the number of shortest paths going from node s to node t and passing through node i.[13] This metric indicates the number of shortest paths going through a node.

4. **Closeness centrality:** $C_i = \frac{\sum_{j \in N, j \neq i} \sigma_{ij}}{(n-1)}$, where N is the set of all nodes in the network, n is the number of nodes, σ_{ij} is the shortest path between node i and node j. This metric is the average distance from a given starting node to all other nodes in the network.[13]

5. **Closeness vitality:** The change of distances between all node pairs when excluding that node.[4]

6. **Clustering coefficient:** $CC_i = \frac{\sum_{j,k} a_{ij} a_{ik} a_{jk}}{k_i(k_i - 1)}$, where a_{ik} is the connection between node i and node k, a_{jk} is the connection between node j and node k. This metric gives an overall indication of how nodes are embedded in their neighborhood.

7. **Core number:** The largest value *k* of a *k-core* containing that node, where a *k-core* is a maximal subgraph that contains nodes of degree *k* or more.[1]

8. **Eccentricity:** The maximum distance from this node to all other nodes in the network.

9. **Eigenvector centrality:** It is the eigenvector for the largest eigenvalue of the adjacency matrix. Nodes with high eigenvector centrality also connect to other nodes which have high eigenvector centrality.

10. **HITS authority:** Measures how valuable information stored in one node is, based on incoming links.[19]

11. **HITS hub:** Estimates how valuable information stored in one node is, based on links.[19]

12. **Load centrality:** The total amount of the commodity passing through a node during all these exchanges.[5] It is the fraction of all shortest paths passing through that node.

13. **Page rank:** A ranking of the nodes based on the structure of the incoming links.

14. **Triangles:** The number of triangles which include a node as one vertex.

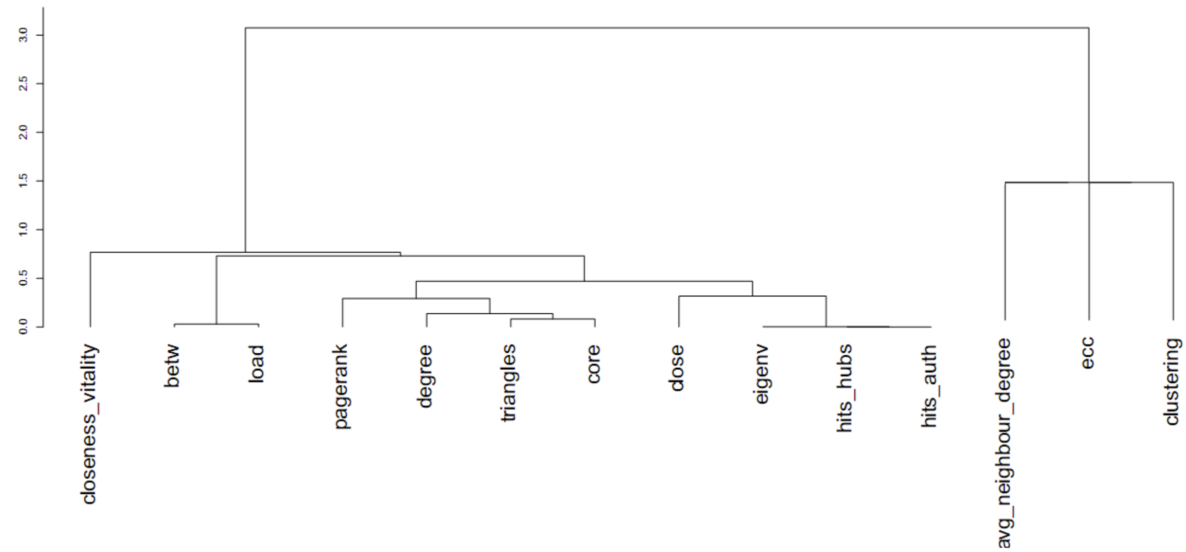


Figure 1: Hierarchical clustering among the fourteen metrics

We compute the hierarchical clustering for the fourteen metrics and the results are presented in Figure 1. The cluster method is based on the group average with Euclidean distance. The hierarchical clustering is dynamic depending on the threshold value of the Euclidean distance. When the Euclidean distance is bigger than 1.35, there are two giant clusters among the fourteen metrics. When the Euclidean distance is between 0.75 and 1.35, there are four clusters: Closeness vitality from the first giant cluster, and three criteria (clustering coefficient, eccentricity, and average neighbor degree) from the second giant cluster. When the Euclidean distance is between 0.45 and 0.75, there are seven clusters: Closeness vitality, betweenness, page rank, closeness, and three criteria from the second giant cluster. When the Euclidean distance is between 0.125 and 0.45, there are nine clusters: Degree, betweenness centrality, closeness centrality, closeness vitality, eigenvector centrality, and page rank, and three criteria from the second giant cluster.

In this paper, we consider four scenarios based on the Euclidean distance in the hierarchical clustering:

- **Four criteria**: Closeness vitality from the first giant cluster, and three criteria (clustering coefficient, eccentricity, and average neighbor degree) from the second giant cluster.
- **Seven criteria**: Closeness vitality, betweenness, page rank, closeness, and three criteria from the second giant cluster.
- **Nine criteria**: Degree, betweenness centrality, closeness centrality, closeness vitality, eigenvector centrality, page rank, and three criteria from the second giant cluster.
- **Thirteen criteria**: All criteria listed above (Note that the HITS authority and the HITS hub are equivalent for undirected graph.)

III.B. Preferences elicitation by Entropy method

Preference information represents a decision maker's attitude in favor of one criterion over another when choosing between alternatives. There are several techniques for eliciting the preference information: direct assignment method,[17] eigenvector method,[27] entropy method,[17] Simple Multi-Attribute Rating Technique (SMART),[11] Kano's model,[35] and distance-to-target method.[23]

In this paper, we select the Entropy method because it can derive objective weights for the multiple metrics.[9] With the input data represented by a decision matrix, the weights of criteria w_j can be calculated by Equation 1,[17] where p_{ij} is the value of the j-th criterion $(i = 1, 2, ..., m, j = 1, 2, ..., n)$, E_j is the entropy of the j-th criterion, d_j is the degree of diversity of the information involved in the j-th criterion.

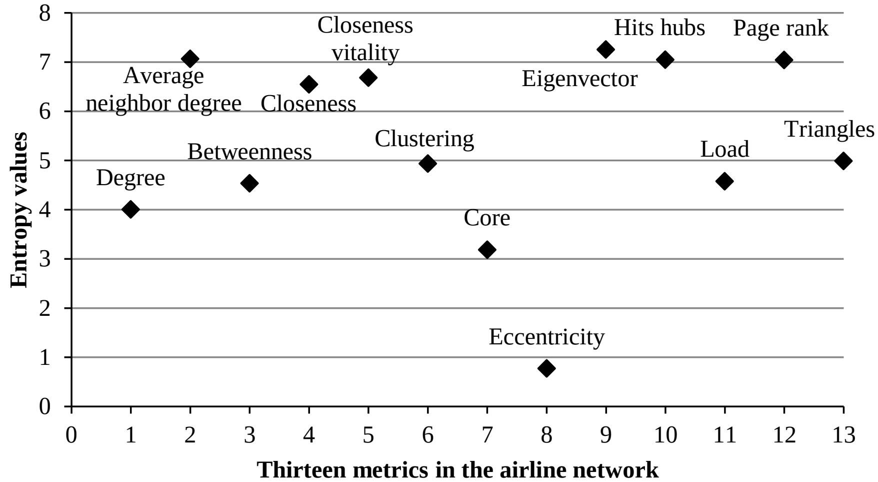


Figure 2: Entropy values for the thirteen metrics in an airline network

$$
\begin{aligned}
& w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, \ \ \forall j \\
& d_j = 1 - E_j, \ \ \forall j \\
& E_j = -\frac{1}{\ln m} \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \ \ \forall j \\
& p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}, \ \ \forall i, j
\end{aligned} \tag{1}
$$

The entropy method helps to investigate contrasts between sets of data, that is, the weight of a criterion is small when all the alternatives have similar values on the criterion. In other words, a criterion does not contribute much when the criterion has similar values for all alternatives.

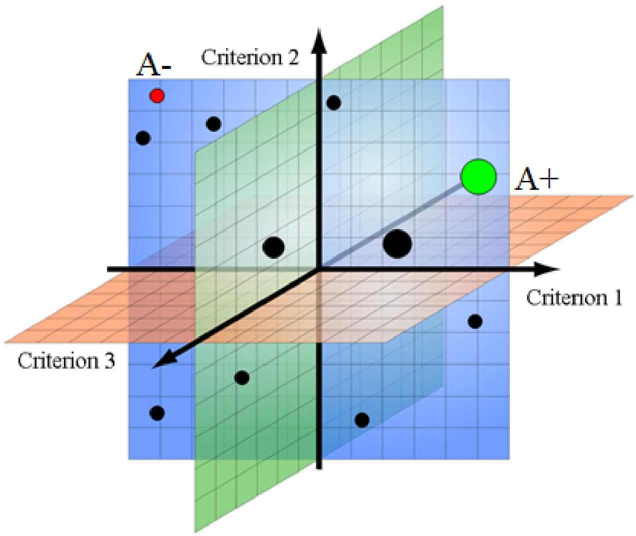
Figure 2 shows the entropy values for the thirteen metrics in the airline network. We can observe that the nodes have similar eccentricity (smallest entropy value 0.7696), while the eigenvector centrality of the nodes differ significantly (largest entropy value 7.2523).

III.C. Improved MCDA to maintain ranking consistency

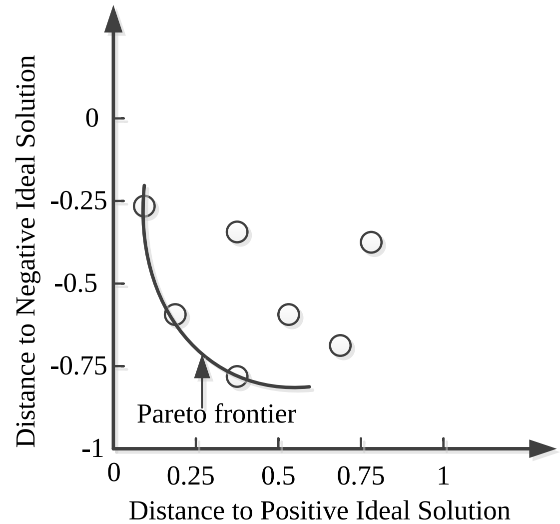
TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the widely used decision analysis methods considering its simplicity and systematic calculation procedures. TOPSIS is based on the idea that the best alternative should have the shortest Euclidean distance to the positive ideal solution A^* and the furthest Euclidean distance from the negative ideal solution A^-.[17] For the purpose of illustration, we can imagine that TOPSIS puts the alternatives into a coordinate system. For example, if there are three criteria, it is a three-dimension coordinate system, as shown in Figure 3 (a). TOPSIS ranks the alternatives based on the Euclidean distance to these two ideal solutions.

Another approach is to visualize the relative closeness of each alternative to the ideal solutions via Pareto frontier, as illustrated in Figure 3 (b), where the horizontal axis represents the distance to the positive ideal solution (S_i), while the vertical axis stands for the distance to the negative ideal solution with minus signal ($-S_n$). The minus signal is used to convert the preference direction of S_n for the convenience of displaying Pareto frontier. The Pareto frontier approach does not need to aggregate the relative closeness, however, instead of one best alternative, a set of non-dominated alternatives is often obtained.

The original TOPSIS method suffers from the ranking inconsistency problem. In this research, we apply an Improved TOPSIS (ITOPSIS) method to assess the node importance in complex networks, where the positive ideal solution and negative ideal solution are set beforehand to maintain ranking consistency.[29]



(a) TOPSIS with three criteria



(b) Pareto Frontier for TOPSIS

Figure 3: TOPSIS Method[17]

III.D. Identify important nodes via Pareto Frontier

The Pareto Frontiers for the four scenarios using ITOPSIS with entropy based weights are shown in Figure 4. Instead of only showing the top-10 ranked nodes as in the previous work,[10] the Pareto Frontier helps to identify a set of important nodes, without of the requirement of setting the number of important nodes from a decision maker beforehand. For example, we can observe from Figure 4 (a) that there are seven top-ranked nodes which should be analyzed further in the airline network.

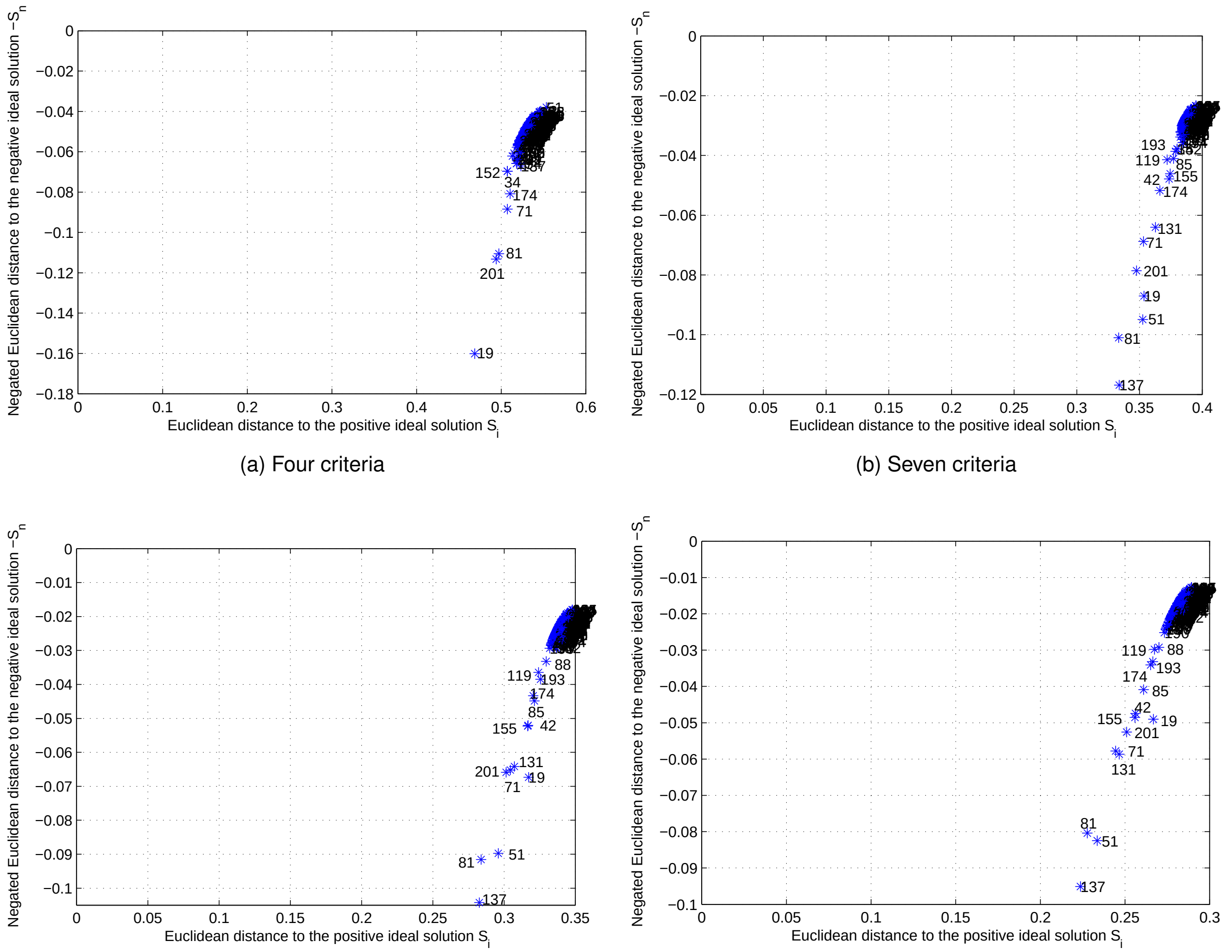
III.E. Uncertainty assessment for the preferences

We perform the sensitivity analysis for the top ranked node using binary search algorithm and the results are shown in Figure 5, where $R1$ represents the node which ranks first among the 235 nodes. The weighting factors for the four scenarios based on the Entropy method are shown in Table 1.

The binary search technique has been widely used to find a target value in a sorted (usually ascending) sequence efficiently.[22,32] This technique compares the middle element of the sorted sequence to the target value, if the middle element is equal to the target value, then the search terminates. If the target value is less than middle element, then the algorithm eliminates the right half of the sorted sequence and conducts the same search for the left side. If the target value is bigger than the middle element, then the algorithm ignores the left half of the sorted sequence and performs the same search for the right side. Otherwise, we can conclude that the target value is not in the sorted sequence. Based on the iterative binary search algorithm, we perform uncertainty assessment for the weighting factors in order to answer the questions: How sensitive the ranking of the most important node is to variations in the current weighting factors of the multiple criteria?

The iterative binary search algorithm varies one input variable at a time in order to find the minimum change which can alter the ranking of two alternatives. It can provide good insights about the range of an input variable when the ranking of the alternatives preserves. It can also tell a decision maker which input variable is more sensitive to the ranking of the alternatives and more attention needs to be paid to the value of this input variable.

Table 2 summarize the top ranked 14 nodes and the most sensitive weight factor which can reverse the top ranked node ($R1$). Surprisingly, we find that the weighting factor of closeness vitality is the most sensitive criterion to the best ranked node in the four scenarios. For instance, when considering four criteria, when decreasing the weighting factor of closeness vitality 64%, the top ranked node $R1$ (*Node 19*) is reversed with the sixth ranked node $R6$ (*Node 34*).



(a) Four criteria (b) Seven criteria

(c) Nine criteria (d) Thirteen criteria

Figure 4: Pareto Frontiers for the four scenarios using ITOPSIS with entropy weights

Table 1: Entropy based weighting factors for the four scenarios

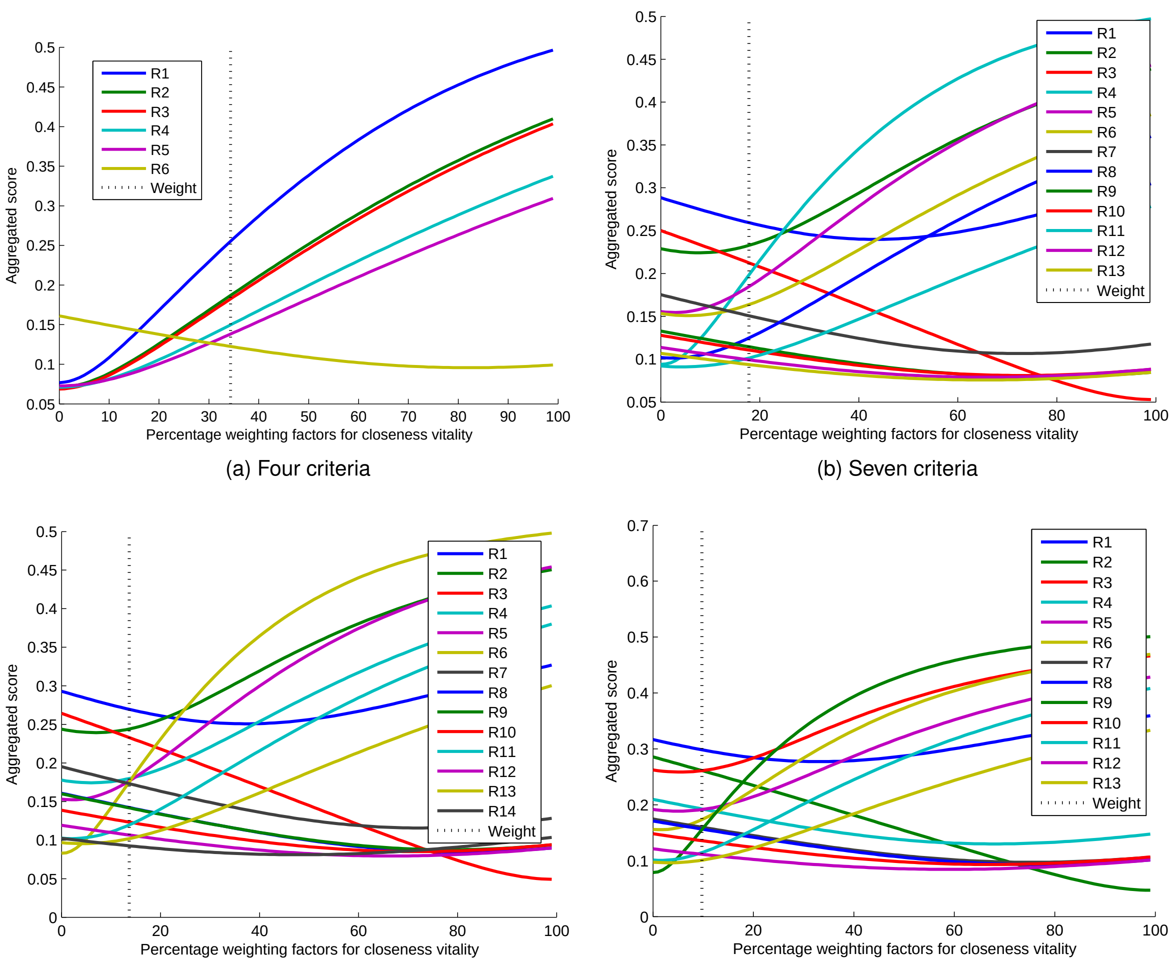
Metrics	**4 Criteria**	**7 Criteria**	**9 Criteria**	**13 Criteria**
Average neighbor degree	0.3633	0.1881	0.1447	0.1030
Betweenness	0	0.1206	0.0928	0.0661
Closeness	0	0.1742	0.134	0.0954
Closeness vitality	0.3435	0.1779	0.1369	0.0974
Clustering	0.2537	0.1313	0.1011	0.0719
Core	0	0	0	0.0464
Degree	0	0	0.0819	0.0583
Eccentricity	0.0396	0.0205	0.0158	0.0112
Eigenvector	0	0	0.1486	0.1057
Hits hubs	0	0	0	0.1027
Load	0	0	0	0.0667
Page rank	0	0.1874	0.1442	0.1026
Triangles	0	0	0	0.0727

III.F. Ranking consistency for TOPSIS with different metrics

In this paper, we assess the ranking consistency and irregularity issues using five measures, based on the works of Matsumoto [21] and Chen.[7] The results are summarized in Figure 6.

Table 2: Top 14 nodes for the four scenarios using ITOPSIS with entropy weights

Rank	**4 Criteria**	**7 Criteria**	**9 Criteria**	**13 Criteria**
R1	19	137	137	137
R2	201	81	81	51
R3	81	51	51	81
R4	71	19	71	131
R5	174	201	201	71
R6	34	71	19	201
R7	152	131	131	155
R8	137	174	42	42
R9	17	42	155	19
R10	154	155	85	85
R11	59	119	174	174
R12	74	85	193	193
R13	221	193	119	119
R14	119	34	88	88
Rank	closeness vitality	closeness vitality	closeness vitality	closeness vitality
Reversal	R1:R6 (-64%)	R1:R4 (52%)	R1:R2 (72%)	R1:R3 (134%)



(a) Four criteria

(b) Seven criteria

(c) Nine criteria

(d) Thirteen criteria

Figure 5: Sensitivity analysis for the four scenarios using ITOPSIS with entropy weights

TOP1 and TOP3 nodes in the four scenarios

	4 Criteria	7 Criteria	9 Criteria	13 Criteria
4 Criteria	1	0	0	0
7 Criteria		1	1	1
9 Criteria			1	1
13 Criteria				1

TOP10% nodes in the four scenarios

	4 Criteria	7 Criteria	9 Criteria	13 Criteria
4 Criteria	1	1	1	1
7 Criteria		1	1	1
9 Criteria			1	1
13 Criteria				1

Overlap10% nodes in the four scenarios

	4 Criteria	7 Criteria	9 Criteria	13 Criteria
4 Criteria	100%	75%	38%	29%
7 Criteria		100%	63%	54%
9 Criteria			100%	92%
13 Criteria				100%

Inversion rate in the four scenarios

	4 Criteria	7 Criteria	9 Criteria	13 Criteria
4 Criteria	0%	25%	39%	45%
7 Criteria		0%	15%	22%
9 Criteria			0%	8%
13 Criteria				0%

Figure 6: Summary of the ranking consistency and irregularity in an airline network

- **TOP1:** The entry is 1 if the best-ranked node in one scenario is also the best-ranked node in another scenario.
- **TOP3:** The entry is 1 if top 3 ranked nodes in one scenario lie in the top 3 ranked nodes in another scenario.
- **TOP10%:** The entry is 1 if the top-ranked node in one scenario lies in the top 10% ranked nodes in another scenario.
- **Overlap10%:** The number of nodes in both the top 10% ranked nodes in one scenario and another scenario, divided by the number of nodes.
- **Inversion rate:** Without considering the middle of the ranking order, better alternatives denote the first half alternatives in the ranking and worse alternatives denote the last half alternative in the ranking. The inversion occurs when a better alternative ranked by one scenario becomes a worse one in another scenario.

We can observe that for the top 1 and top 3 ranked nodes, rankings are consistent when more criteria are considered in the evaluation process. In the TOP10% matrix, all entries are 1. This indicates that in the four scenarios, top-ranked nodes in one scenario lie in the top 10% ranked nodes in another scenario. The overlap rates for the top 10% ranked nodes becomes less when more criteria are considered. There are often switches between better alternatives and worse alternatives in the four scenarios. Therefore, we can conclude that there is no *best* or *worst* alternative, it always depends the objective of the assessment, which criteria need to be considered, and what are the preferences of decision makers.

IV. Conclusions

In this study, we proposed a new methodology incorporating Multiple Criteria Decision Analysis (MCDA) techniques to assess node importance in air transportation networks. First, the correlation among a large set of metrics was investigated in order to identify independent metrics. Second, preferences among multiple metrics were derived based on the Entropy method. Third, an improved MCDA method which can maintain the ranking consistency of the alternatives was applied. In the end, uncertainty assessment for the preferences among the multiple metrics was performed. Moreover, ranking consistency and irregularity issues were reported as well. Our new methodology was used to assess node importance in an airline network. Future work could focus on applying MCDA techniques to compare the performances of different types of network.[30]

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