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VIKOR based Methodology using Local and Global Centralities to Detect Spreaders in Complex Network

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Abstract

The identification of node spreaders is of great importance for influence maximization in complex networks. Nodes that have a high degree, high eigenvector, high betweenness, and high closeness have been identified as spreaders in previous research. Centralities that can be computed using local information of the node have low time complexity but don't consider the whole network. Centralities that use global information of the network can't be applied to large-scale networks and have more time complexity although their high accuracy. In this paper, we propose a novel integrated methodology that combines local and global centralities with the MCDM technique "VIKOR" to synthesize the spreaders nodes. To validate the proposed methodology, we test it on real networks, and the obtained results are satisfactory and prove that it behaves well to find the spreaders nodes in these networks.

Keywords: *spreaders, influence maximization, complex networks, MCDM technique*

Introduction

Complex networks refer to all the entities that are linked to each other, and can be modeled by graphs where the entities are represented by nodes and the links by edges. This modeling facilitates the study and the understanding of their structure by using graph theory. The notion of complex networks is widespread in several fields such as social networks, biological networks, information networks, and transportation networks (Boccaletti et al. 2006). In complex networks, Nodes are structured in a heterogeneous manner which means nodes don't have the same importance in the network. One of the most challenging topics in network science is node importance. With the control of these nodes, we can broadcast messages or information more quickly in the network as we can reduce the spread of an epidemic like the case of covid19. Understanding this broadcasting process is a very interesting topic in different fields including viral marketing and disease transmission. With the appearance of publicly available data, the analysis of complex networks plays a more important role than before in different areas. There has been a lot of research done in the past to figure out how important nodes are from the aspect of centrality-based methods.

These methods have some limitations either it considers the whole system but it has a higher cost and it does not work in large-scale networks (Weimann 1991) or it is simple and it has low temporal complexity but it does not consider the whole system (Sheikhahmadi, Nematbakhsh, et Shokrollahi 2015). The degree method is classified as a local method. It relies exclusively on communications between a node and its neighbors. Nodes that have a high degree can be spreaders of information in the local neighborhood, but they would not be able to spread information globally unless it is linked to other spreaders nodes (Kitsak et al. 2010). On the other hand, nodes with high betweenness centrality, or high closeness or high coreness would be essential for spreading information across the network, and it could not be powerful locally due to its local connections. Betweenness, closeness, and katz are classified as a global method. They are computationally labour-consuming because they require the entire graph in the computation. Bae and Kim (Bae et Kim 2014) proposed neighborhood coreness centrality to calculate a node's spreading influence in a network by adding all of its neighbors' k-shell values. LeaderRank LR also a global method was proposed by Lü et al. (Lü et al. 2011) during the calculation of the importance of the node. LR does not consider the outgoing links, it considers just the incoming links. Chen et al. (D.-B. Chen et al. 2013) proposed ClusterRank CR to identify spreaders in directed networks. It considers the effects of local clustering on

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information transmission. Yu et al.(Yu et al. 2019) proposed Profit Leader approach taking in account the network structure. This approach is based on nodes' profit capability. Available resources, and sharing probability are used in the calculation of the profit capability.

Other approaches based on gravity formula like Extended Gravity Centrality EGC proposed by Ma et al.(Ma et al. 2016), and Local Gravity Model LGM proposed by Li et al.(« Identifying influential spreaders by gravity model | Scientific Reports » s. d.). EGC is based on the global structure of the network. It's a combination of the values of k shell, the shortest distance between nodes, and the formula for gravity. LGM is based on degree values, gravity formula, and the shortest distance between nodes. The shortcoming of these two approaches that they take time for large graphs by calculating the shortest distance between nodes. Recently, there are some approaches that have appeared that use local and global information of the network. For instance, Liu et al.(Liu, Wang, et Deng 2020) suggested the Generalized Mechanics Model GMM that use local and global information to identify the importance of nodes. This approach requires the calculation of eigenvectors and the shortest distance between nodes which takes more time. Zhao et al.(Zhao, Wang, et Deng 2020) presented the global importance of node GIN. The calculation of the importance of node using GIN take into account the global importance and self-importance of node but it still has a lack of precision. Global and Local Structure GLS proposed by Sheng et al.(Sheng et al. 2020) take into consideration the local and global influence of nodes to calculate their influence. All of these methods are summarized in Table 1.

Table 1: A summary of the approaches proposed to identify influential nodes.

Author's	Methodology	Type of network	shortcomings
Freeman (Freeman 1978)	Degree centrality	Directed, unweighted	It is simple and it has low temporal complexity but it does not consider the whole system
Newman (Newman 2005)	Betweenness centrality	Undirected,weighted	Computationally labour-consuming because they require the entire graph in the computation
Freeman (Freeman 1978)	Closeness centrality	Undirected, weighted	Computationally labour-consuming because they require the entire graph in the computation
Bonacih et al.(Bonacich et Lloyd 2001)	Eigenvector centrality	Undirected, unweighted	Counts only important links.
Bae and Kim (Bae et Kim 2014)	neighborhood coreness centrality	Undirected, unweighted	Consider local structure of the network.
Lü et al.(Lü et al. 2011)	LeaderRank LR	Directed, unweighted	LR does not consider the outgoing links, it considers just the incoming links.
Chen et al.(D.-B. Chen et al. 2013)	ClusterRank CR	Directed, weighted	Use local information.
Yu et al. (Yu et al. 2019)	Profit Leader PL	Undirected,unweighted	The method's accuracy is insufficient for locating the network's influential nodes.
Ma et al.(Ma et al. 2016)	Extended Gravity Centrality EGC	Undirected,unweighted	Requires more time for large networks when calculating the shortest distances between nodes.
Li et al.(« Identifying influential spreaders by gravity model | Scientific Reports » s. d.)	Local Gravity Model	Undirected,unweighted	this method contains a free parameter that can affect the performance of the method, not applicable for large scale networks
Liu et al.(Liu, Wang, et Deng 2020)	Generalized Mechanics Model GMM	Undirected, unweighted	This approach includes the calculation of eigenvectors and the shortest distance between nodes, which is time-consuming.
Zhao et al.(Zhao, Wang, et Deng 2020)	global importance of node GIN	Undirected, unweighted	The closeness centrality has a significant influence on this approach, which might reduce its accuracy.
Sheng et al.(Sheng et al. 2020)	Global and Local Structure GLS	Undirected, unweighted	The method's precision is insufficient for large graphs.

Even though, there are various kinds of centrality measures to decide the most spread nodes of a network, there's not yet an agreement pipeline in the discipline of network science to choose and execute the best suitable measure for a given network. In this context, we will take advantage of using the Multi-criteria decision problem MCDM that can help us to use several indices at the same time to synthesize the importance of a node (S.-J. Chen et Hwang 1992). MCDM techniques were applied in different fields like the investment decision (Erdogan et Naumčik 2019), selection of suppliers (Uppala et al. 2017), choice of transportation(Nassereddine et Eskandari 2017). Bian et al. (Bian, Hu, et Deng 2017) introduced AHP in the field of network science to gather multi-attribute for the evaluation of each node's influence. Du et al.(Du et al. 2014) applied TOPSIS in the first time to identify influential nodes in complex networks. Hu et al. (Hu et al. 2016) improved the original TOPSIS to Weighted TOPSIS by proposing a new algorithm to calculate the weight of each attribute. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje)(Opricovic et Tzeng 2004) as one of MCDM techniques, has gotten a lot of attention as a way to deal with complex issues including conflict factors. It's applied in lean management for the tool selection (Jing, Niu, et Chang 2019), for the ranking of mathematical instructional videos (Acuña-Soto, Liern, et Pérez-Gladish 2019), water resource management (Opricovic 2009). VIKOR is used in this paper for the first time to assemble some measures of pioneering centralities to take advantage of local measurements and the advantages of global measurements and to achieve a certain balance.

The remainder of this paper is structured in the following manner. In section 2, some preliminaries of centralities, VIKOR, and numerical example are presented. Section 3 introduced the spreader detection methodology. Section 4 present the experimental analysis of this methodology. Finally, section 5 puts this paper to a close.

2. Preliminaries

In this section, we present centrality measures, and VIKOR with numerical example to explain the model. We take degree centrality, betweenness centrality, closeness centrality, and Eigenvector centrality as multi attributes in the proposed methodology.

Pioneers' researches have introduced a lot of centrality measures to identify spreaders nodes in complex networks. A node centrality metric calculates a node's topological impact in networks. In general, these methods can be divided into two categories local centrality and global Centrality.

In complex networks, a graph structure is used to describe systems. We consider an undirected graph *G = (V, E)* with V a set of nodes, and E a set of edges, $|V| = n$, and $|E| = m$. Let $A = (a_{i,j}) = n * m$ be the adjacency matrix, where $(a_{i,j}) = 1$ if vertex *i* is linked to *j* and 0 otherwise.

2.1 Local centrality

2.1.1. Degree centrality

The degree is the simplest measure of centrality. It keeps track of how many links each node has. It's a local measure. It completely ignores to consider the rest of the network (Freeman 1978).

$$C_D(u) = \sum_j^N X_{uj} \quad (1)$$

The total number of nodes is *N*, *u* is the concerned node. *j* represents all the other nodes, and X_{uj} represents the link between nodes *u* and *j*.

2.1.2. Eigenvector Centrality

The eigenvector centrality is an extension of degree centrality. Eigenvector centrality consider the total number of adjacent nodes Furthermore, it consider the importance of the adjacent node. It measure the degree of the vertex as well as the degree of its neighbors (Bonacich et Lloyd 2001).

$$x_v = \frac{1}{\gamma}\sum_{t\in M(v)} x_t = \frac{1}{\gamma}\sum_{t\in G} a_{v,t}x_t \quad (2)$$

Where $M(v)$ is a set of the neighbors of v and γ is a constant.

2.2 Global centrality

2.2.1. Betweenness Centrality

The betweenness centrality counts how many shortest paths a node is a part of, meaning that it functions as a crossing point (Ulrik Brandes 2001).

$$C_B(u) = \sum_{j,k\neq u} \frac{g_{jk}(u)}{g_{jk}} \quad (3)$$

Where: g_{jk} means the total number of shortest paths connecting nodes *j* and *k*.
$g_{jk}(i)$ is the total number of shortest paths between nodes *j* and *k* that pass through node *i*.

2.2.2 Closeness Centrality

The closeness centrality measure of how close is a node to the other nodes. It's a reverse of the sum of the shortest path distances (Ulrik Brandes 2001).

$$C_C(u) = \left[\sum_j^N d_{uj}\right]^{-1} \quad (4)$$

d_{uj} represents the distance between node *u*, and node *j.*

2.2.3 Katz centrality

The Katz centrality was launched in 1953 to calculate a node's power by Leo Katz (Katz 1953). It provides shortest paths different weights based on their lengths. Shorter paths are preferred, since they are more essential for information flow than longer paths. Contribution of a path of length F is directly proportional to s^F. It's defined as:

$$K = sA + s^2A^2 + s^3A^3 + \ldots + s^FA^F + \cdots = (I - sA)^{-1} - I \quad (5)$$

With $s \in (0,1)$ and *I* a unit matrix.

2.2.4 Coreness centrality

The coreness of node *u* defined with Equation (6), if *u* is a part of a subgraph *H (V1, E1),* with the most connections (Seidman 1983).

$$C_s(u) = i \quad (6)$$

Where $\forall\, u, u \in V_1, and\ k_u \geq i$, and in the induced subgraph H, k_u is the degree of u.

2.2.5 Page Rank centrality

Page Rank calculates a node's importance based on the importance of its neighbors. Brin and Page suggested the first method for calculating PageRank in 1998, while working on the ranking module for the Google prototype (Brin et Page 2012). A Pagerank of a node is defined as:

$$P(u) = \frac{q}{n} + (1-q)\sum_{v:v\to u} {P(v)}/{k_v^{out}} \quad (7)$$

n is the total number of nodes in the network, k_v^{out} is the out-degree of node v, q is a teleportation factor, and $v \to u$ demonstrates a link from v to u.

2.3 VIKOR model

The VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method is a multi-criteria decision making (MCDM) or multi-criteria decision analysis method (Opricovic et Tzeng 2004). Serafim Opricovic invented it to solve decision-making problems with inconsistent and non-commensurable criteria (different units), assuming that the compromise is reasonable for resolving the conflict, the decision-maker needs the closest solution of the ideal, and alternatives are evaluated against all pre-determined criteria. VIKOR classifies the alternatives and decides the best option called compromise which is most close to the ideal. Po-Lung Yu and Milan Zeleny presented the concept of a compromise solution in MCDM in 1973. In his doctorate, S. Opricovic developed the basic ideas of VIKOR. In 1979, he completed a dissertation, and in 1980, he submitted an application. In 1990, the word VIKOR was introduced from the Serbian VlseKriterijumska Optimizacija I Kompromisno Resenje, which translates to "Multi-criteria optimization and compromise solution" (Abbas Mardani et al).

The MCDM problem is formulated as follows: Determine the best (compromise) solution in the multicriteria sense from the set of J feasible alternatives $A_1, A_2, \ldots A_J$, evaluated according to the set of n criteria functions. The elements f_{ij} of the decision matrix are the input data with f_{ij} denoting the value of the *i-th* criterion function for the alternative A_J.

The VIKOR procedure consists of the following steps:

Step 1: Determine the best values f_i^* and the worst f_i^- of all the criterion functions with *i = 1,2, ..., n*;

f_i^* = *max* (f_{ij}, *j = 1,..., J*) f_i^- = *min* (f_{ij}, *j = 1,..., J*)	if the *i-th* function is beneficial and otherwise for cost function

Step2: Calculate S_j, and R_j values, *j = 1, 2, ..., J,* based on the relations 8 and 9:

$$S_j = \sum_{i=1}^{n} W_i\ (f_i^* - f_{ij})/(f_i^* - f_i^-) \quad (8)$$

$$R_j = \max_i\left[W_i\ (f_i^* - f_{ij})/(f_i^* - f_i^-)\right] \quad (9)$$

With W_i is the weight of the criteria expressing its importance, and *j=1,2,…J*

Step 3: Calculate the values Q_j, *j = 1, 2, ..., J*, based on the relations 10,11,12,13 and 14.

$$Q_j = \frac{v(S_j - S^*)}{(S^- - S^*)} + \frac{(1-v)(R_j - R^*)}{(R^- - R^*)} \quad (10)$$

$$S^* = \min(S_j, j = 1, \ldots J) \quad (11)$$

$$S^- = \max(S_j, j = 1, \ldots J) \quad (12)$$

$$R^* = \min(R_j, j = 1, \ldots J) \quad (13)$$

$$R^- = \max(R_j, j = 1, \ldots J) \quad (14)$$

and v is adopted as the weight of the maximum group utility strategy, whereas 1−v is the weight of the individual regret.

Step 4: order the alternatives, by *S*, *R*, and *Q* values, starting from the minimum value. Three ranking lists are the results.

Step 5. If the following two conditions are reached, As a compromise solution, suggest variant *A(1)* which is best classified by the measure *Q* (minimum).

C1: "Acceptable advantage":

Q (A (2) - Q (A (1))> = DQ where: *A(2)* is the alternative with the second position in the ranking list by *Q* and *DQ = 1 / (J -1).*

C2. "Acceptable stability in decision making":

Alternative *A(1)* must also be ranked highest by *S* or / and *R*. If one of the conditions is not reached, a set of compromise options is proposed, which includes:

- Alternatives *A(1)* and *A(2)* if only condition C2 is not fulfilled, or
- If condition C1 is not fulfilled, the alternatives *A(1), A(2), A(3),..., A(M), A(M)* is defined by the relation $Q(A(M)) - Q(A(1)) < DQ$ for maximum M (the positions of these alternatives are "in closeness").

2.4 Numerical application of VIKOR

In light of the above model proposed, the Krackhardt kite network is presented to explain how this model acts in its part. The kite network is a simple graph with ten nodes as shown in Fig.1. In 1990, Krackhardt presents this graph in order to determine different concepts of centrality (David Krackhardt, s. d.). Centrality measures of nodes are calculated using R software and presented in Table 2.

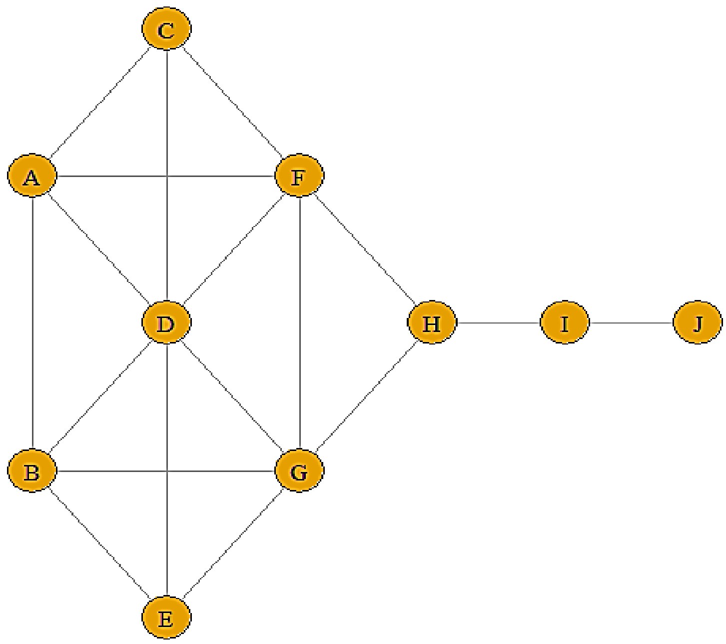


Fig.1.The kite network

Table 2: The values of centrality measures of kite's members

Nodes	DC	BC	CC	EC
A	4	0.833333	0.05882353	0.73221232
B	4	0.833333	0.05882353	0.73221232
C	3	0.000000	0.05555556	0.59422577
D	6	3.666667	0.06666667	1.00000000
E	3	0.000000	0.05555556	0.59422577
F	5	8.333333	0.07142857	0.82676381
G	5	8.333333	0.07142857	0.82676381
H	3	14.000000	0.06666667	0.40717690
I	2	8.000000	0.04761905	0.09994054
J	1	0.000000	0.03448276	0.02320742

Firstly we determine the best values f_i^* and the worst f_i^- of all the criterion as shown in Table 3. Then we calculate the utility measure S_j and the regret measure $R_j$value using the formula number 5 and 6 (see Table 4). After, we calculate S_j, R_j, and from these elements we can calculate S^*, R^*, $R^-$and $S^-$to extract finally the value of *Q*. S^* *= 0,174158,* R^**=0,080952,* R^-*= 0,3,* S^- *= 1* and by using formulas described in step 3 (previous section), we calculate Q as presented in Table 5 and we can rank nodes based on Q values.

From Table 5 and Figure 1, F and G have approximatively the same importance due to their position as a cross point to pass to the second side of the network. So, they positioned as the most influential nodes. D as a facilitator in kite's network, it should be rank at the following. H in fourth rank as a link between the two parts of the network. A, B, C, and E come after because of their position at the periphery of the network, and node J undoubtedly at the last of ranking after node I because of its position at the margin of the network.

Table 3: the best and the worst values of all the criterion

Nodes	DC	BC	CC	EC
A	4	0.833333	0.05882353	0.73221232
B	4	0.833333	0.05882353	0.73221232
C	3	0.000000	0.05555556	0.59422577
D	6	3.666667	0.06666667	1.00000000
E	3	0.000000	0.05555556	0.59422577
F	5	8.333333	0.07142857	0.82676381
G	5	8.333333	0.07142857	0.82676381
H	3	14.000000	0.06666667	0.40717690
I	2	8.000000	0.04761905	0.09994054
J	1	0.000000	0.03448276	0.02320742
Best f_i^*	6	14.000000	0.07142857	1.00000000
Worst f_i^-	1	0.000000	0.03448276	0.02320742

Table 4: the value of S_j and R_j of all nodes of kite's network

Nodes	DC	BC	CC	EC	Sj	Rj
A	4	0.833333	0.05882353	0.73221232	0,568578	0,329167
B	4	0.833333	0.05882353	0.73221232	0,568578	0,329167
C	3	0.000000	0.05555556	0.59422577	0,68037	0,35
D	6	3.666667	0.06666667	1.00000000	0,303444	0,258333
E	3	0.000000	0.05555556	0.59422577	0,68037	0,35
F	5	8.333333	0.07142857	0.82676381	0,201667	0,141667
G	5	8.333333	0.07142857	0.82676381	0,201667	0,141667
H	3	14.000000	0.06666667	0.40717690	0,225111	0,18
I	2	8.000000	0.04761905	0.09994054	0,615556	0,24
J	1	0.000000	0.03448276	0.02320742	1	0,35

Table 5: The rank of each node of kite's network

Nodes	S_j	R_j	Q	rank
A	0,452693	0,188095	0,413202	5
B	0,452693	0,188095	0,413202	6
C	0,573513	0,2	0,513526	7
D	0,186286	0,147619	0,159517	3
E	0,573513	0,2	0,513526	8
F	0,174158	0,080952	0	2
G	0,174158	0,080952	0	1
H	0,340739	0,182072	0,331673	4
I	0,715481	0,276433	0,773946	9
J	1	0,3	1	10

3. The proposed methodology

Many researchers have spent years trying to come up with the best method to select spreaders. Although there are several centrality methods, there's not yet an agreement pipeline for the selection of the best suitable method. MCDM techniques are also used in this context specially AHP and TOPSIS. In this study, a novel methodology is applied for the first time to detect spreaders in complex networks. This methodology consists of combining centrality measures with VIKOR. Two phases of methodology, has been applied for the detection of spreaders (as shown in Fig.2) could be summarized as follows: The first phase is allocated to the choice of complex network for the study, the choice of local and global centrality measures and the calculation of node's centralities. In the second phase, we have the data (centrality values) to establish the decision matrix. According to this decision matrix, we can extract the best and worst values. We assign weights for criteria (centrality measures). In this proposed methodology, we attribute weigh P_1 for local centralities and P_2 for global centralities, with $P_1 < P_2$, and we calculate the regret value and the utility value. By using these two values we can calculate the index Q, having a ranking list, and verify the compromise solution.

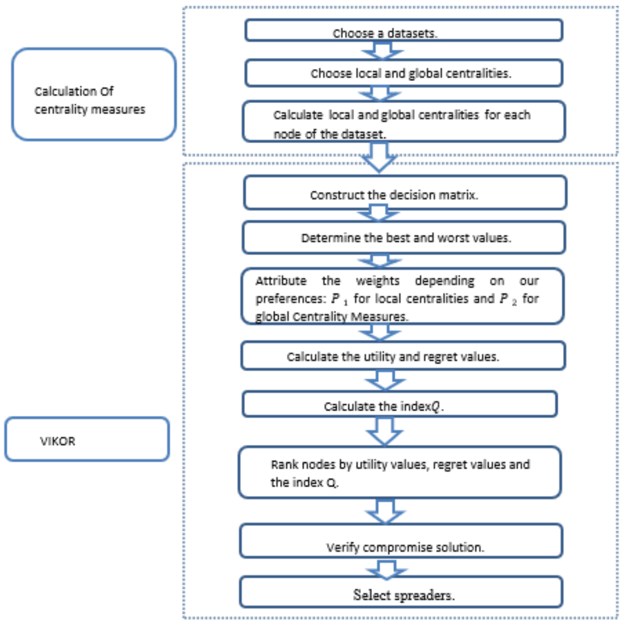


Fig.2. The flowchart of the proposed methodology.

4. Experimental analysis

In this section we will apply the proposed methodology on real networks to see the results on real data.

Datasets

To evaluate the effectiveness of the proposed methodology, we use eight real networks. These datasets are described below.

(i) Zachary club is a famous social network that defines the relationships between 34 members in a karate club (« M. Girvan and M. E. J. Newman, “Community structure in social and biological networks,” Proceedings of the National Acadamy of Sciences of the United States of America,vol.99,no », s. d.).
(ii) rfid: is a records of contacts among patients and different sorts of medical care laborers in the geriatric unit of a hospital in Lyon, France.
(iii) Macaque Monkey is a directed graph model of the visuotactile brain areas and connections of the macaque monkey. The model consists of 45 areas and 463 edges.
(iv) Immno: Immunoglobulin interaction network. It is composed of 1316 vertices and 6300 edges.
(v) Football: is a network of soccer teams which participated in the World Championship in Paris (« M. Girvan and M. E. J. Newman, “Community structure in social and biological networks,” Proceedings of the National Acadamy of Sciences of the United States of America,vol.99,no », s. d.).
(vi) Yeast: is a network that contain 2361 nodes and 7182 connections in this protein-protein interaction network.
(vii) Usair97: air transportation network. Airports in the United States are represented by nodes, and air travel links between them are represented by edges (Colizza, Pastor-Satorras, et Vespignani 2007).
(viii) Netscience: collaboration network that represent co-authorship of scientists in network theory and experiments (Newman 2006).

The properties of these datasets are presented in Table 6.

Table 6: Some topological properties of the applied datasets

Network	Nodes number	Edges number	Max degree	Average degree	Density
Karate	34	78	17	4.5882	0.1390
Macaque	45	463	40	20.58	0.2338
Immuno	1316	6300	17	9.574	0.0072
rfid	75	32424	4286	864.6	11.68432
football	35	118	19	6.743	0.1983193
yeast	2361	7182	66	6.084	0.002577908
Usair97	332	2126	139	12.81	0.03869253
Netscience	1589	2742	34	3.451	0.002173317

Discussion and experiment

Experiment 1: Compare the top ten lists between centrality measures and VIKOR

To demonstrate the efficiency of the proposed model, DC, BC, CC and EC are taken for comparison. The lists of top ten influential nodes for these network using centralities and VIKOR are shown in Tables 7, 8 and 9.

In kite’s network, the results between the proposed methodology and DC or EC have the same nine members in the top ten lists (see Table 8). The proposed methodology and BC have the same six members on the top ten lists. The proposed methodology and CC have the same five members in the top ten lists. In Macaque network (see Table 8), there are the same ten members in the top ten lists by comparing the proposed methodology and CC. There are the same nine members in the top ten lists by comparing the proposed methodology and DC. There are eight members in the top ten lists by comparing the proposed methodology and EC and six members by comparing the proposed method with BC. In Immuno (see Table 8), the proposed methodology and EC have four same nodes in the top ten lists and no same nodes exist by comparing the proposed methodology and DC, CC and BC.

In rfid network (see Table 9), there are eight members of top ten nodes between the proposed methodology and BC and EC, nine nodes between the proposed methodology and CC and seven nodes between the proposed methodology and DC. For Football (see Table 9), the results between the proposed methodology and EC or BC have the same seven nodes of the top ten lists. There are the same eight nodes by comparing the proposed methodology and DC and six nodes by comparing the proposed methodology and CC. the results of Usair97 have the same nine, eight, and six nodes respectively between the proposed methodology and DC, BC and EC and no one’s between the proposed methodology and CC.

According to Table 7, in yeast network, comparing the top ten nodes of the proposed methodology and DC, five of their top ten lists are the same. Between the proposed methodology and CC three nodes are the same. Between the proposed methodology and BC two are the same and seven between the proposed methodology and EC. For Netscience network, there are four, three, two and eight same nodes respectively between our proposed method and DC, CC, BC and EC in their top ten lists.

By using this comparison of top ten lists which seems these measures of centralities and VIKOR on real networks, it’s sur that the results of ranking lists of centrality measures and the proposed methodology are different.

Table 7: The top-10 nodes ranked by the proposed methodology, DC, CC, BC, and EC in yeast and Netscience networks

	yeast					Netscience				
Rank	DC	CC	BC	EC	The proposed methodology	DC	CC	BC	EC	The proposed methodology
1	566	549	147	442	302	33	756	756	33	34
2	209	784	1443	252	252	34	78	34	34	33
3	302	199	784	135	492	78	758	78	30	54
4	1443	302	566	126	120	54	757	225	54	30
5	784	1443	209	165	126	294	562	516	53	53
6	147	566	549	302	442	1429	34	150	132	132
7	120	492	302	492	61	1430	72	216	133	133
8	492	209	508	138	644	1431	762	94	1550	756
9	644	283	2022	131	135	62	763	72	131	78
10	252	252	120	1249	138	216	150	281	561	1550

Table8: The top-10 nodes ranked by the proposed methodology, DC, CC, BC, and EC in Karate, Macaque and immuno networks

Karate					
Rank	DC	CC	BC	EC	The proposed methodology
1	John A	Mr Hi	Mr Hi	John A	John A
2	Mr Hi	John A	John A	Actor 3	Mr Hi
3	Actor 33	Actor 20	Actor 20	Actor 33	Actor 33
4	Actor 3	Actor 13	Actor 32	Mr Hi	Actor 3
5	Actor 2	Actor 21	Actor 33	Actor 2	Actor 32
6	Actor 32	Actor 32	Actor 3	Actor 9	Actor 2
7	Actor 4	Actor 29	Actor 25	Actor 14	Actor 9
8	Actor 9	Actor 33	Actor 2	Actor 24	Actor 14
9	Actor 14	Actor 9	Actor 18	Actor 32	Actor 4
10	Actor 24	Actor 3	Actor 7	Actor 4	Actor 8
Macaque					
1	5	30	15	13	15
2	15	13	30	29	30
3	13	15	5	18	5
4	29	29	38	9	13
5	30	27	37	10	29
6	18	5	13	15	18
7	10	18	29	5	27
8	9	10	27	3	10
9	27	9	42	8	9
10	2	8	17	12	8
Immuno					
1	1072	438	1095	692	694
2	414	1097	1092	691	696
3	691	1095	438	747	692
4	4	439	436	748	745
5	6	437	1097	707	747
6	33	1100	434	746	743
7	34	1096	1099	706	706
8	49	440	445	693	746
9	97	436	448	749	695
10	173	1099	435	976	744

Table 9: The top-10 nodes ranked by the proposed methodology, DC, CC, BC, and EC in rfid, football, and usair97 networks

rfid					
Rank	DC	CC	BC	EC	The proposed methodology
1	7	1	23	7	7
2	29	23	15	29	29
3	37	7	7	27	27
4	27	17	37	37	37
5	15	37	17	5	23
6	23	29	27	23	5
7	17	5	29	64	17
8	30	15	1	17	64
9	11	64	11	21	15
10	13	11	45	13	1
Football					
1	10	2	13	12	12
2	18	10	10	18	18
3	12	18	12	14	10
4	13	12	18	34	14
5	14	13	2	10	13
6	24	35	5	26	25
7	25	8	14	25	35
8	35	11	8	1	2
9	8	9	7	5	34
10	2	26	28	16	5
USAIR97					
1	118	166	8	248	261
2	261	182	261	201	118
3	255	118	166	47	166
4	152	181	182	118	182
5	182	172	118	67	67
6	230	167	47	261	201
7	166	163	152	313	152
8	67	168	67	255	47
9	112	164	201	311	255
10	201	158	13	109	230

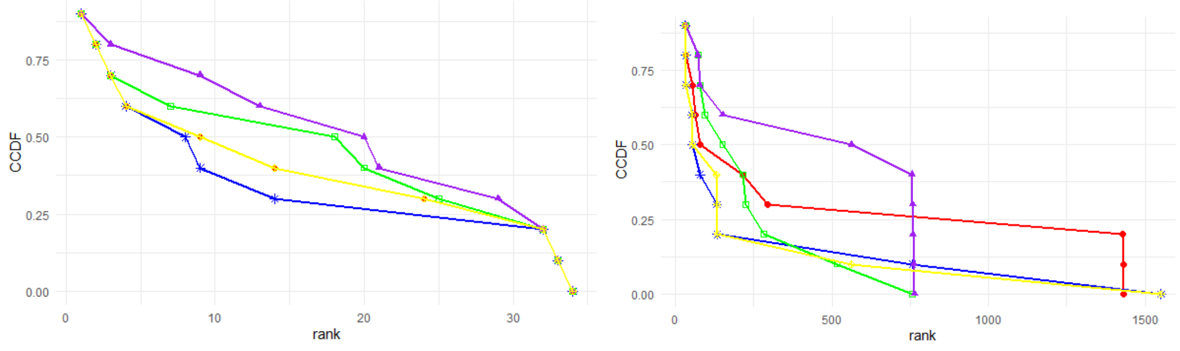
Experiment 2: Discriminability

Complementary cumulative distribution function (CCDF) is a standards used to discriminate nodes. The discriminability is well defined if the CCDF plot is slowly going down which means q tends to n. The value of CCDF is specified using this Equation(12).(Rai et al. 2021)

$$CCDF(q) \quad = 1 - \frac{\sum_{i=1}^{q} n_i}{n} \tag{12}$$

The CCDF curves by the proposed methodology and other four centralities on karate and netscience networks are plotted in Fig.2. The choice of these two networks attributed to their different size and structures.

In Karate network, the CCDF curves of the proposed methodology overlap EC, BC and CC from the first to the fourth rank and also at the last rank from 32th to 34th. DC and EC coincide with each other from the first to the last rank. In Netscience network, the proposed methodology and EC agree with each other excluding some few nodes. CC and BC lost efficacy about the 750th to the last rank and DC don't distinguish the 1376th to the 1589th.



(a) karate (b) Netscience

DC The proposed methodology CC BC EC

Fig.2. CCDF curves are plotted to rank spreader nodes in karate, and Netscience networks

Conclusion

In complex networks, detecting the spreaders nodes is still an open issue. Until now, several approaches have been proposed in this context but there is still a lack of accuracy. We suggest in this paper, a new methodology for the first time in solving this kind of problem. VIKOR combines local and global centralities as multi attributes to find spreaders in such networks. The results show that the proposed methodology is accepted in terms of this identification of spreaders. In future projects, other methods can be combined with VIKOR to confirm more accuracy for the decision-making process.

References

[1]. Abbas Mardani , Edmundas Kazimieras Zavadskas Kannan Govindan , et Aslan Amat Senin and Ahmad Jusoh s. d. « VIKOR Technique: A Systematic Review of the State of the Art Literature on Methodologies and Applications ».

[2]. Acuña-Soto, Claudia Margarita, Vicente Liern, et Blanca Pérez-Gladish. 2019. « A VIKOR-Based Approach for the Ranking of Mathematical Instructional Videos ». *Management Decision* 57 (2): 501-22. https://doi.org/10.1108/MD-03-2018-0242.

[3]. Bae, Joonhyun, et Sangwook Kim. 2014. « Identifying and Ranking Influential Spreaders in Complex Networks by Neighborhood Coreness ». *Physica A: Statistical Mechanics and Its Applications* 395 (février): 549-59. https://doi.org/10.1016/j.physa.2013.10.047.

[4]. Bian, Tian, Jiantao Hu, et Yong Deng. 2017. « Identifying Influential Nodes in Complex Networks Based on AHP ». *Physica A: Statistical Mechanics and Its Applications* 479 (août): 422-36. https://doi.org/10.1016/j.physa.2017.02.085.

[5]. Boccaletti, S, V Latora, Y Moreno, M Chavez, et D Hwang. 2006. « Complex Networks: Structure and Dynamics ». *Physics Reports* 424 (4-5): 175-308. https://doi.org/10.1016/j.physrep.2005.10.009.

[6]. Bonacich, Phillip, et Paulette Lloyd. 2001. « Eigenvector-like Measures of Centrality for Asymmetric Relations ». *Social Networks* 23 (3): 191-201. https://doi.org/10.1016/S0378-8733(01)00038-7.

[7]. Brin, Sergey, et Lawrence Page. 2012. « Reprint of: The Anatomy of a Large-Scale Hypertextual Web Search Engine ». *Computer Networks* 56 (18): 3825-33. https://doi.org/10.1016/j.comnet.2012.10.007.

[8]. Chen, Duan-Bing, Hui Gao, Linyuan Lü, et Tao Zhou. 2013. « Identifying Influential Nodes in Large-Scale Directed Networks: The Role of Clustering ». *PLoS ONE* 8 (10). https://doi.org/10.1371/journal.pone.0077455.

[9]. Chen, Shu-Jen, et Ching-Lai Hwang. 1992. « Fuzzy Multiple Attribute Decision Making Methods ». In *Fuzzy Multiple Attribute Decision Making*, par Shu-Jen Chen et Ching-Lai Hwang, 375:289-486. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-46768-4_5.

[10]. Colizza, Vittoria, Romualdo Pastor-Satorras, et Alessandro Vespignani. 2007. « Reaction–Diffusion Processes and Metapopulation Models in Heterogeneous Networks ». *Nature Physics* 3 (4): 276-82. https://doi.org/10.1038/nphys560.

[11]. David Krackhardt. s. d. « Assessing the Political Landscape: Structure, Cognition, and Power in Organizations ».

[12]. Du, Yuxian, Cai Gao, Yong Hu, Sankaran Mahadevan, et Yong Deng. 2014. « A New Method of Identifying Influential Nodes in Complex Networks Based on TOPSIS ». *Physica A: Statistical Mechanics and Its Applications* 399 (avril): 57-69. https://doi.org/10.1016/j.physa.2013.12.031.

[13]. Erdogan, Seyit Ali, et Andrej Naumčik. 2019. « Evaluation of Investing in Real Estate in EU and Non-EU Countries Based on MCDM ». In . Vilnius Gediminas Technical University. https://doi.org/10.3846/mbmst.2019.151.

[14]. Freeman, Linton C. 1978. « Centrality in Social Networks Conceptual Clarification ». *Social Networks* 1 (3): 215-39. https://doi.org/10.1016/0378-8733(78)90021-7.

[15]. Hu, Jiantao, Yuxian Du, Hongming Mo, Daijun Wei, et Yong Deng. 2016. « A Modified Weighted TOPSIS to Identify Influential Nodes in Complex Networks ». *Physica A: Statistical Mechanics and Its Applications* 444 (février): 73-85. https://doi.org/10.1016/j.physa.2015.09.028.

[16]. « Identifying influential spreaders by gravity model | Scientific Reports ». s. d. Consulté le 11 juin 2021. https://www.nature.com/articles/s41598-019-44930-9.

[17]. Jing, Shuwei, Zhanwen Niu, et Pei-Chann Chang. 2019. « The Application of VIKOR for the Tool Selection in Lean Management ». *Journal of Intelligent Manufacturing* 30 (8): 2901-12.

[18]. Katz, Leo. 1953. « A New Status Index Derived from Sociometric Analysis ». *Psychometrika* 18 (1): 39-43. https://doi.org/10.1007/BF02289026.

[19]. Kitsak, Maksim, Lazaros K. Gallos, Shlomo Havlin, Fredrik Liljeros, Lev Muchnik, H. Eugene Stanley, et Hernán A. Makse. 2010. « Identification of Influential Spreaders in Complex Networks ». *Nature Physics* 6 (11): 888-93. https://doi.org/10.1038/nphys1746.

[20]. Liu, Fan, Zhen Wang, et Yong Deng. 2020. « GMM: A generalized mechanics model for identifying the importance of nodes in complex networks ». *Knowledge-Based Systems* 193 (C). https://doi.org/10.1016/j.knosys.2019.105464.

[21]. Lü, Linyuan, Yi-Cheng Zhang, Chi Ho Yeung, et Tao Zhou. 2011. « Leaders in Social Networks, the Delicious Case ». Édité par Enrico Scalas. *PLoS ONE* 6 (6): e21202. https://doi.org/10.1371/journal.pone.0021202.

[22]. « M. Girvan and M. E. J. Newman, "Community structure in social and biological networks," Proceedings of the National Acadamy of Sciences of the United States of America,vol.99,no ». s. d.

[23]. Ma, Ling-Ling, Chuang Ma, Hai-Feng Zhang, et Bing-Hong Wang. 2016. « Identifying influential spreaders in complex networks based on gravity formula ». *Physica A: Statistical Mechanics and its Applications* 451 (juin): 205-12. https://doi.org/10.1016/j.physa.2015.12.162.

[24]. Nassereddine, M., et H. Eskandari. 2017. « An Integrated MCDM Approach to Evaluate Public Transportation Systems in Tehran ». *Transportation Research Part A: Policy and Practice* 106 (décembre): 427-39. https://doi.org/10.1016/j.tra.2017.10.013.

[25]. Newman, M. E. J. 2006. « Finding Community Structure in Networks Using the Eigenvectors of Matrices ». *Physical Review E* 74 (3): 036104. https://doi.org/10.1103/PhysRevE.74.036104.

[26]. Newman, M.E. J. 2005. « A Measure of Betweenness Centrality Based on Random Walks ». *Social Networks* 27 (1): 39-54. https://doi.org/10.1016/j.socnet.2004.11.009.

[27]. Opricovic, Serafim. 2009. « A Compromise Solution in Water Resources Planning ». *Water Resources Management* 23 (8): 1549-61. https://doi.org/10.1007/s11269-008-9340-y.

[28]. Opricovic, Serafim, et Gwo-Hshiung Tzeng. 2004. « Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS ». *European Journal of Operational Research* 156 (2): 445-55. https://doi.org/10.1016/S0377-2217(03)00020-1.

[29]. Rai, K. Ait, T. Agouti, M. Machkour, et J. Antari. 2021. « Identification of Complex Network Influencer Using the Technology for Order Preference by Similarity to an Ideal Solution ». *Journal of Physics: Conference Series* 1743 (janvier): 012004. https://doi.org/10.1088/1742-6596/1743/1/012004.

[30]. Seidman, Stephen B. 1983. « Network Structure and Minimum Degree ». *Social Networks* 5 (3): 269-87. https://doi.org/10.1016/0378-8733(83)90028-X.

[31]. Sheikhahmadi, Amir, Mohammad Ali Nematbakhsh, et Arman Shokrollahi. 2015. « Improving detection of influential nodes in complex networks ». *Physica A: Statistical Mechanics and its Applications* 436: 833-45.

[32]. Sheng, Jinfang, Jinying Dai, Bin Wang, Guihua Duan, Jun Long, Junkai Zhang, Kerong Guan, Sheng Hu, Long Chen, et Wanghao Guan. 2020. « Identifying Influential Nodes in Complex Networks Based on Global and Local Structure ». *Physica A: Statistical Mechanics and Its Applications* 541 (C). https://ideas.repec.org/a/eee/phsmap/v541y2020ics0378437119318308.html.

[33]. Ulrik Brandes. 2001. « A faster algorithm for betweenness centrality ». *The Journal of Mathematical Sociology,* 2001.

[34]. Uppala, Akshay Kumar, Rishabh Ranka, J. J. Thakkar, Manupati Vijay Kumar, et Shilpa Agrawal. 2017. « Selection of Green Suppliers Based on GSCM Practices: Using Fuzzy MCDM Approach in an Electronics Company ». Handbook of Research on Fuzzy and Rough Set Theory in Organizational Decision Making. IGI Global. 2017. https://doi.org/10.4018/978-1-5225-1008-6.ch016.

[35]. Weimann, Gabriel. 1991. « The Influentials: Back to the Concept of Opinion Leaders? » *Public Opinion Quarterly* 55 (2): 267. https://doi.org/10.1086/269257.

[36]. Yu, Zhongjing, Junming Shao, Qinli Yang, et Zejun Sun. 2019. « ProfitLeader: identifying leaders in networks with profit capacity ». *World Wide Web* 22 (2): 533-53. https://doi.org/10.1007/s11280-018-0537-6.

[37]. Zhao, Jie, Yunchuan Wang, et Yong Deng. 2020. « Identifying Influential Nodes in Complex Networks from Global Perspective ». *Chaos, Solitons & Fractals* 133 (C). https://ideas.repec.org/a/eee/chsofr/v133y2020ics0960077920300369.html.