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RESEARCH ARTICLE

Generalization of Relative Change in a Centrality Measure to Identify Vital Nodes in Complex Networks

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ABSTRACT Identifying vital nodes is important in disease research, spreading rumors, viral marketing, and drug development. The vital nodes in any network are used to spread information as widely as possible. Centrality measures such as Degree centrality (D), Betweenness centrality (B), Closeness centrality (C), Katz (K), Cluster coefficient (CC), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality) centrality measures can be used to effectively quantify vital nodes. The majority of these centrality measures are defined in the literature and are based on a network's local and/or global structure. However, these measures are time-consuming and inefficient for large-scale networks. Also, these measures cannot study the effect of removal of vital nodes in resource-constrained networks. To address these concerns, we propose the six new centrality measures namely GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK. We develop these measures based on the relative change of the clustering coefficient, degree, and Katz centralities after the removal of a vertex. Next, we compare the proposed centrality measures with D, B, C, CC, K, PR, LGC, and ISC to demonstrate their efficiency and time complexity. We utilize the SIR (Susceptible-Infected-Recovered) and IC (Independent Cascade) models to study the maximum information spread of proposed measures over conventional ones. We perform extensive simulations on large-scale real-world data sets and prove that local centrality measures perform better in some networks than global measures in terms of time complexity and information spread. Further, we also observe the number of cliques drastically improves the efficiency of global centrality measures.

INDEX TERMS Complex networks, influential nodes, local centrality, relative change in centrality.

I. INTRODUCTION

The centrality measure effectively quantifies the network's influential nodes. Identifying powerful or vital nodes is critical in many networking applications, including disease research [1], [2], fake news spreading [3], viral marketing [4], drug development, opinion monitoring [5], biological field [6], fraud detection [7], structural design [8], social physics [9], and other fields [10]. In [1], authors analyzed the centrality measures for a disease transmission network and shown that relatively simple ego-network-based network measures can be adequate to measure the spread of the disease. Authors proposed a spreading scheme for viral marketing in [4] by using different centrality measures and some of the research insights presented to design marketing schemes. Various centrality measures have been proposed in [6] to identify the central nodes in large networks. It was also shown that data can be reduced using machine learning

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methods to choose appropriate centrality measures. This is the most meticulously researched fundamental concept in the network science. In the literature, the centrality measure is defined in a variety of ways. According to [11], it is defined as the information or traffic contained in all possible paths between pairs of nodes. These measures can be viewed as mathematical heuristics for identifying prominent nodes in networks based on local or global structural properties [12]. The centrality measures make certain assumptions about the process in which information flows through a network [13]. In the last several decades, many centrality methods have been proposed to find the seed nodes (vital nodes). Various centrality measures, such as Degree centrality (D), Betweenness centrality (B) [14], Closeness centrality (C) [13], Katz (K) [15], PageRank (PR) [16], have been proposed in the literature [17]. The centrality measures were broadly classified into three types: local measures, global measures, and random-walk measures [18]. The degree is a local metric with low accuracy because it focuses on first-order neighbors. The information from the global network is ignored by the local metrics. The global metrics are betweenness and closeness, and these are considered the nodes' global information. These global metrics, however, necessitate more computational time for large-scale networks [19].

PageRank is a random-walk measure that provides better performance and is appropriate for directed networks. All of these metrics rank nodes based on their prominence in the network. A node with high centrality in a social network, for example, may represent a powerful personality. The majority of these centrality measures are defined by the number of paths that connect pairs of nodes, the shortest paths, betweenness, degree, page rank, and so on. Several centrality measurements are computed using local and global information from network nodes. However, for large-scale complex networks, these measures are time-consuming, costly, and inefficient. One of the interesting research directions in this area is developing centrality measures that consider node removal and neighborhood-level scenarios. When influential nodes fail for any reason, nodes should consider the alternate path or nearest neighbors, to find the important nodes. These centrality measures find numerous applications in many real-time networks. In [20], authors proposed the centrality measures to study the National Airspace System, and airport network subjected to natural hazards. They have noted that node removal according to dynamic centrality measures can have faster collapse rates. Authors proposed a link centrality measure in [21] based on topological and electrical properties of power grid networks. They study the attack vulnerability of power grids in network failures. In [22], authors used centrality measures to reduce interference rate and congestion around the influential nodes in Software-Defined Aerial Networks. Detecting the central nodes which can be a base station can reduce the overall energy consumption in multi-hop wireless networks [23]. In [24], authors discussed the statistical measurements in constantly changing cooperative communities to identify the most significant invaders. This work is motivated by these applications in the areas of cascading failures, natural hazards, and network congestion.

II. RELATED WORK

This section briefly discusses the recent works on centrality measures in the literature. Authors have proposed trust PageRank (TPR) [25], nearest neighborhood trust-PageRank (NTPR) [26], extended cluster coefficient ranking measure (ECRM) [27], and normalised local centrality measure (NLC) [28] using local and global network information. The ECRM of a node is defined based on the correlation between a node and its neighbors. By utilising the structure of the local network around a node and the influence feedback from the node's closest neighbors, Zhao et al. [28] concentrated on normalised local centrality. Xin et al. [29] proposed a heterogeneity-oriented immunization measure based on individual heterogeneity and network topology factors. Lellis and Porfiri [30] designed an algorithm for detecting influential nodes in network dynamic systems using time series. A community-based mediator (CbM) [31] is presented as a metric for identifying influential nodes in a vast and complex network, taking into account the entropy of a random walk from a node to every community. The local and global centrality is proposed by the authors [32] which is defined based on degree and shortest distance between a pair of nodes. A centrality based on isolation of vertex proposed by authors [33].

The degree cluster coefficient method (DCC) [34] is used for identifying influential nodes that takes into account degree, clustering coefficient, and neighbors. The basic centralities and machine learning techniques are used to find the vital nodes using SIR and the independent cascade model [35]. The local relative change of average shortest path (LRASP) [36] is proposed depending on the network's local structure. Based on the relative change in the average shortest path (ASP) in the local network when the node is removed, the LRASP measure for a node is calculated. From the LRASP measure, we generalised the relative change in centralities based on the global and local structures to find the vital nodes. A new parallel algorithm is proposed in [23] to find all central nodes by obtaining Breadth First Search trees. Authors proposed a belief propagation and node reinsertion method in [37] to identify the vital nodes. A novel centrality measure based on fuzzy concept is proposed in [38] which considered the idea of inner structure of node's box. In [39], authors presented a comparative study of two vertex deleted centrality measures namely Laplacian centrality and algebraic centrality and proved that algebraic centrality is easier to compute than Laplacian centrality. None of these works focused on developing centrality measures which considers local and global information for node removal cases using clustering coefficient, degree, katz centralities.

In this work, we focus on deriving centrality measures to identify the vital node with maximal information spread and minimal time complexity. For this purpose, we propose six new centrality measures in this paper: GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK. These proposed methods focus on both local and global average structural information. We propose generalised centrality measures based on the relative change in degree, Katz, and clustering coefficient after node removal. GRAD, GRACC, and GRAK are generalized global centrality measures based on the relative change in degree, clustering coefficient, and Katz, respectively. Similarly, local centrality measures are denoted as LRACC, LRAD, and LRAK. The proposed methods were compared to the standard measures available in the literature, such as D, B, C, CC, K, PR, LGC, and ISC.

A. ORGANISATION

This paper is organized as follows. We define the basic centrality measures in section III. Section IV presents the proposed centrality measures and corresponding algorithms. Section V is devoted to the data sets, spreading models, and assessment approaches utilized to prove the efficiency of our measures. Section VI includes discussions and the experimental findings. Finally, Section VIII provides important insights, conclusions, and future directions.

III. PRELIMINARIES

First, we define some benchmark centrality measures in this section. Any graph or network is denoted by G, formulated as $G = (V, E)$, where V represents nodes and E represents edges. For computing the vital nodes in networks several centralities are represented in the existing work, such as degree (D), betweenness (B), closeness (C), and clustering coefficient (CC) centralities are defined as follows: The degree centrality (D) [40] is considered as number of direct ties between one vertex to other vertices. The average length of the shortest path connecting a node to all other nodes in the graph is known as Closeness centrality (C) [41]. The C of node v can be defined as

$$C(v) = \frac{1}{\sum\limits_{u \in V} d(v, u)}$$

where $d(v, u)$ indicates the shortest path distance between u, v nodes. The betweenness centrality (B) [14] is global centrality and it considers the shortest path through the node. The B of node w can be defined as

$$B(w) = \sum_{u \neq v \neq w \in V} \frac{d_{uv}(w)}{d_{uv}}$$

where d_{uv} is the distance from the vertex u to vertex v, $d_{uv}(w)$ is the path between vertices u and v that passes via vertex w is the shortest. The number of closed triplets over the total number of triplets is used to calculate the clustering coefficient centrality (CC) [42], [43].

$$CC(v) = \frac{2N_v}{d_v(d_v - 1)}$$

where N_v is number of links between neighbors of v, d_v is degree of node v. In the Katz centrality (K) of a network, the relative influence of each node is calculated by taking first level neighboring and next level neighboring nodes that are connected with first level neighboring nodes. The K of a node v_i is computed as

$$K(v_i) = \alpha \sum_{j=1}^{n} A_{i,j} K(v_j)$$

where α is dumping factor (considered to be less than largest eigen value).

PageRank (PR): A popular variation of the eigenvector centrality technique, called PageRank centrality is presented in [44] and [45]. In the Google search engine and other commercial applications, PR is used to rank the websites.

$$PR_v^t = \frac{1-\alpha}{n} + \alpha \sum_{v_i \in N_v} \frac{PR_{v_i}^{t-1}}{k_{v_i}}$$

where n represents vertices, N_v represents vertex v neighbors, α is jump probability, k_{v_i} is the number of vertices to which the vertex v_i points, and t is the iterative parameter. The first term in PageRank is for regularising the PageRank. Here, the sum will converge to one when the second term reaches its maximum.

Local and Global Centrality (LGC): The LGC [32] is defined based on the degree and shortest path between a pair of vertices. It is a combination of the local and global influence of a vertex. The LGC of node v is defined as follows:

$$LGC(v) = \frac{d_v}{n} \times \sum_{v \neq u} \frac{\sqrt{d_u + \alpha}}{d(u, v)}$$

where d_v represents the degree of node v, n is total number of nodes, $d(u, v)$ is the shortest distance between u and v, and α is the parameter and range between 0 and 1. First part indicates the local influence and second part indicates the global influence.

Isolating Centrality (ISC): The ISC [33] of a node is defined as the product of its degree and isolated coefficient. The ISC of a node is calculated as:

$$ISC(v) = | N_v \cap D_\delta | \times d_v$$

where N_v is the neighbors of v and D_δ is set of nodes with degree δ, and d_v is degree of node v. The average shortest path (ASP) [43] is defined as the shortest paths for all potential network pairs along with the average number of steps. The ASP measures how well information is effectively transmitted from powerful nodes to all other nodes in the network. The ASP is computed for a graph G, as

$$ASP[G] = \frac{\sum\limits_{u \neq v \in V} d_{uv}}{N(N-1)}$$

where d_{uv} denotes the shortest path from nodes u and v. The relative change in ASP (RASP) [46] can be computed as

$$RASP[k] = \frac{|ASP[G_k'] - ASP[G]|}{ASP[G]}, \quad k = 1, 2, \cdots, N$$

In a graph G, v is a vertex, consider a neighbourhood level L. The LRASP [36] is a local centrality and calculated nodes influence based on the network's local structure. This LRASP metric for a node is based on the relative change in the average shortest path in the local network when the node is eliminated. $N_L(v)$ is the set of all neighbors up to the level L with vertex v. RASP of $G_{N_L}(v)$ will be calculated for an induced subgraph $G_{N_L}(v)$ of graph G with vertex set $N_L(v)$. The summary of the methods is shown in Table 1. The LRASP is computed as follows:

$$LRASP_L[v] = \frac{|ASP[G_{N_L(v)} \setminus v] - ASP[G_{N_L(v)}]|}{ASP[G_{N_L(v)}]},$$

A. CONTRIBUTIONS

1) Firstly, we propose a generalised centrality measure by using the relative change in any centrality. For that, the effect of the centrality measure after deleting a vertex has been exploited.
2) Secondly, we propose six centralities such as GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK and compared with the conventional measures D, B, C, CC, K, PR, LGC, and ISC. Proposed measures are extremely useful to study the complex networks with less computational complexity.
3) Finally, to verify the maximum information spread, we test our centrality measures on real-world data sets using SIR and IC models.

Next we define generalization of the centrality measure using the relative change in the centrality.

IV. GENERALIZATION OF RELATIVE A CHANGE IN CENTRALITY

In this section, we generalize the centrality measure based on the relative change in the centrality. We propose this generalization of the centrality measure of a vertex in the network by using the effect of the centrality measure after removing a vertex. The centralities of a node defined in the literature are based on network local structure and global structure. But we defined the local and global centrality measures of a node by observing the effect of the relative change in any centrality once the node is removed. Furthermore, we list local and global centrality measures based on this generalization. The summary of our proposed methods and existing methods are shown in Table 1.

Consider any centrality $\mathscr{C}$, for every vertex we can find the values by using this centrality $\mathscr{C}$ and also we can find the average centrality value for graph and it is denoted as Avg$\mathscr{C}$. We can define two measures, global and local, based on the effect of relative change. It means we investigate the effect of relative change of Avg$\mathscr{C}$ once the vertex is removed. The global measure is defined as follows:

$$GRAvg\mathscr{C}(v) = \frac{|Avg\mathscr{C}[G'_v] - Avg\mathscr{C}[G]|}{Avg\mathscr{C}[G]} \tag{1}$$

where G'_v is a network after removing the vertex v from network G. The centrality $GRAvg\mathscr{C}$ is global for finding the

Algorithm 1 Algorithm for Finding Global Measure $GRAvg\mathscr{C}(v)$ for a Vertex in Graph G

Input: Graph $G = (V, E)$, vertex v
Output: Global measure ($GRAvg\mathscr{C}(v)$) of a vertex v

```
begin
    V = nodelist, E = edgelist
    for every vertex v in V do
        find C(v)
    find AvgC(G)
    similarly find AvgC[G'_v] /* G'_v is a graph after
    removing a vertex v from G */
    find GRAvgC(v) = |AvgC[G'_v] − AvgC[G]| / AvgC[G]
    return (GRAvgC(v))
```

centrality of a vertex in the entire network. Process of finding the $GRAvg\mathscr{C}$ of vertex v of graph G given in Algorithm 1. The global measure defined above based on the global structure and for this measure we need entire network information. Now we define a local measure based on local structure of graph and for this measure we need local network information. Consider the neighbourhood level L for a vertex v in G and $N_L(v)$ is the vertex v of the neighbors up to the level L in the graph. The level L can range from 0 to the graph's diameter. Let us define the local measure which is as follows:

$$LRAvg\mathscr{C}_L(v) = \frac{|Avg\mathscr{C}[G_{N_L(v)} \setminus v] - Avg\mathscr{C}[G_{N_L(v)}]|}{Avg\mathscr{C}[G_{N_L(v)}]}, \tag{2}$$

where $G_{N_L(v)} \setminus v$ is a graph $G_{N_L(v)}$ after deleting a vertex v. Assume a neighbourhood level L for a vertex v in G, $N_L(v)$ is the vertex v of the neighbors up to the level L in the graph. Find the $Avg\mathscr{C}$ of induced subgraph $G_{N_L}(v)$ of graph G with vertex set $N_L(v)$. The centrality $LRAvg\mathscr{C}$ is local for finding the centrality of a vertex by involving only neighboring vertices up to the level L. Process of finding the $LRAvg\mathscr{C}_L$ of a vertex v of graph G is given in Algorithm 2. Next we list local and global centrality measures based on this generalization. We consider the centrality $\mathscr{C}$ as clustering coefficient, degree and Katz centrality which are shown in Table 1.

A. CENTRALITY $\mathscr{C}$ IS CLUSTERING COEFFICIENT

If we consider centrality $\mathscr{C}$ as clustering coefficient (CC) [47] then the average clustering coefficient (ACC) is calculated for graph G as:

$$ACC[G] = \frac{\sum_{v \in V} CC(v)}{N} \tag{3}$$

where $CC(v)$ indicates the clustering coefficient of a node v. The global relative change in average clustering coefficient of a vertex v is defined as:

$$GRACC(v) = \frac{|ACC[G'_v] - ACC[G]|}{ACC[G]},$$

Algorithm 2 Algorithm for Finding Local Measure $LRAvg\mathscr{C}_L(v)$ for a Vertex in Graph G

Input: Graph $G = (V, E)$, vertex v and level L
Output: Local measure ($LRAvg\mathscr{C}_L(v)$) of a vertex v
begin
  $V = nodelist, E = edgelist, n := len(V)$;
  for i *from* 1 *to* L **do**
    find the neighbours of vertex v for each level i and add to the set $N_L(v)$ by using edgelist E.
  Consider $H = G_{N_L(v)}$ /* find induced subgraph of G with set vertex set $N_L(v)$ by using edge list E */
  find $LRAvg\mathscr{C}_L(v) = \frac{|Avg\mathscr{C}[H \setminus v] - Avg\mathscr{C}[H]|}{Avg\mathscr{C}[H]}$
  where $H \setminus v$ is a graph obtained after removing a vertex v from $V(H)$ and we can also find $Avg\mathscr{C}$ of a graph.
  return ($LRAvg\mathscr{C}_L(v)$)

Local relative change in average clustering coefficient for a vertex v of G defined as follows:

$$LRACC_L(v) = \frac{|ACC[G_{N_L(v)} \setminus v] - ACC[G_{N_L(v)}]|}{ACC[G_{N_L(v)}]},$$

B. CENTRALITY $\mathscr{C}$ IS KATZ CENTRALITY

If we consider centrality $\mathscr{C}$ as Katz centrality (K) [15] then average Katz centrality (AK) of graph is determined as:

$$AK[G] = \frac{\sum_{v \in V} K(v)}{N} \quad (4)$$

where $K(v)$ indicates the Katz centrality value of a node v. The global relative change in average Katz centrality can be calculated as:

$$GRAK(v) = \frac{|AK[G'_k] - AK[G]|}{AK[G]}, \quad v \in V$$

Local relative change in average Katz centrality of a vertex v of G defined as follows:

$$LRAK_L(v) = \frac{|AK[G_{N_L(v)} \setminus v] - AK[G_{N_L(v)}]|}{AK[G_{N_L(v)}]},$$

C. CENTRALITY $\mathscr{C}$ IS DEGREE

If we consider centrality $\mathscr{C}$ as degree (D) [48] the average degree is calculated as:

$$AD[G] = \frac{\sum_{v \in V} d_v}{N} \quad (5)$$

where d_v denotes the degree of a node v. The global relative change in average degree of a node v in graph G can be determined as:

$$GRAD(v) = \frac{|AD[G'_v] - AD[G]|}{AD[G]}, \quad v \in V$$

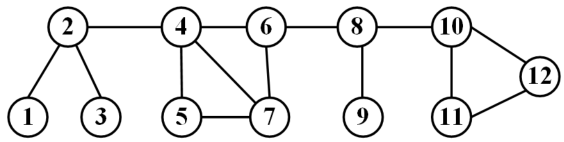

FIGURE 1. Toy Graph with 12 vertices and 14 edges.

Local relative change in average degree of a node v in graph G defined as follows:

$$LRAD_L(v) = \frac{|AD[G_{N_L(v)} \setminus v] - AD[G_{N_L(v)}]|}{AD[G_{N_L(v)}]}$$

Example: We illustrate these proposed centralities by using toy example. Simple graph with 12 vertices and 14 edges is given in the Fig. 1. For the network given in the Fig. 1, we find the centrality D, B, C, CC, K, PR, LGC, ISC, GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK values for every vertex which are given in the Table 2. While finding the local measures (LRACC, LRAD and LRAK), we consider L is half of the diameter.

D. COMPLEXITY OF FINDING $GRAvg\mathscr{C}$ AND $LRAvg\mathscr{C}$

Let us consider the network $G = (V, E)$, where $|V| = n$ denotes the number of nodes and $|E| = m$ represent the number of edges. For a graph G, consider the computational complexity for evaluating the relative change in $Avg\mathscr{C}$ for all vertices as $O(f(n))$. The complexity for finding the global measure $GRAvg\mathscr{C}$ in algorithm 1 is $O(f(n))$. The computational complexity for local centrality $LRAvg\mathscr{C}$ mentioned in algorithm 2 is $O(n^2 + f(|N_L(v)|))$. Here, v denotes number of nodes and $N_L(v)$ represents neighbors of vertex v to the level L. Finding the induced subgraph in a given graph takes run time $O(n^2)$, and finding the $LRAvg\mathscr{C}$ value for this induced subgraph costs $f(|N_L(v)|)$ where $|N_L(v)|$ is the size of the induced subgraph. The level L can range from 0 to the graph's diameter. An alternative way, if L is the graph's diameter, then $LRAvg\mathscr{C}$ equals $GRAvg\mathscr{C}$. In worst-case scenario, the $|N_L(v)|$ value is n. In this paper, we assume that level L is half the diameter of the graph. In the given graph for calculating centrality, $LRAvg\mathscr{C}$ for each vertex, takes $O(n(max\{n^2, f(|N_L(v)|)\}))$. This time complexity is defined by the local structure of each vertex as $max\{n^2, f(|N_L(v)|)\}$. Computing global measure $GRAvg\mathscr{C}$ takes more runtime when compared to local $LRAvg\mathscr{C}$ measure. Computing the $LRAvg\mathscr{C}$ measure for any graph is very efficient. We present the time complexity of the proposed centralities in the Table 4.

The neighborhood level L values can be varied from real value 1 to diameter. We have examined that L is equal to half of the diameter that covers the more local neighbors' information with less time complexity. From our simulation experiments, we have also observed that this particular L value maintains a trade-off between time complexity and maximum information spread. One more interesting finding is when L converges to diameter, it will be a global measure. In our simulations, we have observed

TABLE 1. ***GRAvg𝒞*** **and** ***LRAvg𝒞*** **are proposed centralities, where 𝒞 stands for D (Degree), K (Katz), CC (Clustering Coefficient), and ASP (Average Shortest Path). The Proposed centralities in this work are colored in red.**

Centrality $\mathscr{C}$	$Avg\mathscr{C}$	$GRAvg\mathscr{C}(v)$	$LRAvg\mathscr{C}_L(v)$
D	$AD[G]=\frac{\sum_{v\in V} d_v}{N}$	$GRAD(v)=\frac{\lvert AD[G'_v]-AD[G]\rvert}{AD[G]}$	$LRAD_L(v)=\frac{\lvert AD[G_{N_L(v)}\setminus v]-AD[G_{N_L(v)}]\rvert}{AD[G_{N_L(v)}]}$
K	$AK[G]=\frac{\sum_{v\in V} K(v)}{N}$	$GRAK(v)=\frac{\lvert AK[G'_k]-AK[G]\rvert}{AK[G]}$	$LRAK_L(v)=\frac{\lvert AK[G_{N_L(v)}\setminus v]-AK[G_{N_L(v)}]\rvert}{AK[G_{N_L(v)}]}$
CC	$ACC[G]=\frac{\sum_{v\in V} CC(v)}{N}$	$GRACC(v)=\frac{\lvert ACC[G'_v]-ACC[G]\rvert}{ACC[G]}$	$LRACC_L(v)=\frac{\lvert ACC[G_{N_L(v)}\setminus v]-ACC[G_{N_L(v)}]\rvert}{ACC[G_{N_L(v)}]}$
ASP	$ASP[G]=\frac{\sum_{u\neq v\in V} d_{uv}}{N(N-1)}$	$RASP(G)=\frac{\lvert ASP[G'_v]-ASP[G]\rvert}{ASP[G]}$ [46]	$LRASP(G)=\frac{\lvert ASP[G_{N_L(v)}\setminus v]-ASP[G_{N_L(v)}]\rvert}{ASP[G_{N_L(v)}]}$ [36]

TABLE 2. **D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz) centralities values at a vertex for a graph are shown in Figure 1. Top three influenced nodes are represented in red color.**

Vertex(v)	1	2	3	4	5	6	7	8	9	10	11	12
$D(v)$	1	3	1	4	2	3	3	3	1	3	2	2
$B(v)$	0	0.345	0	0.491	0	0.545	0.55	0.564	0	0.327	0	0
$C(v)$	0.275	0.367	0.275	0.458	0.333	0.478	0.407	0.44	0.314	0.355	0.275	0.275
$K(v)$	0.285	0.291	0.285	0.293	0.288	0.291	0.291	0.291	0.285	0.291	0.288	0.288
$CC(v)$	0	0	0	0.333	1	0.333	0.667	0	0	0.333	1	1
$PR(v)$	0.0460	0.118	0.0460	0.129	0.067	0.097	0.096	0.106	0.043	0.105	0.073	0.073
$LGC(v)$	0.578	2.315	0.578	3.725	1.451	2.752	2.521	2.577	0.623	2.316	1.253	1.253
$ISC(v)$	0	6	0	0	0	0	0	3	0	0	0	0
$GRACC(v)$	0.091	0.169	0.091	0.454	0.065	0.091	0.454	0.403	0.091	0.454	0.454	0.454
$LRACC(v)$	0.010	0.558	0.010	0.091	0.247	0.091	0.091	0.169	0.273	0.636	0.455	0.455
$GRAD(v)$	0.013	0.143	0.013	0.221	0.065	0.143	0.143	0.143	0.013	0.143	0.065	0.065
$LRAD(v)$	0.034	0.111	0.034	0.174	0.030	0.143	0.091	0.167	0.051	0.111	0.091	0.091
$GRAK(v)$	0.045	0.042	0.045	0.046	0.046	0.047	0.045	0.043	0.045	0.042	0.043	0.043
$LRAK(v)$	0.202	0.148	0.202	0.043	0.145	0.047	0.044	0.048	0.149	0.151	0.264	0.264

TABLE 3. **Basic properties of six data sets.**

Network	Nodes	Edges	Max Degree	Avg. Degree	Diameter	Avg. Clustering Coeff.
USAir97	332	2126	139	12.8	6	0.625
bio-celegans	453	2025	237	8.94	7	0.646
ca-netscience	379	914	34	4.82	17	0.741
web-polblogs	643	2280	165	7.09	10	0.232
email-univ	1133	5451	71	9.62	8	0.220
Fb_Pages	14113	52310	215	7	9	0.239

TABLE 4. **Time complexity of finding** ***Avg𝒞***, ***GRAvg𝒞*** **and** ***LRAvg𝒞*** **where 𝒞 is D, K, CC, and ASP, where** d_{max} **is the maximum degree of a network,** n **(**m**) number of vertices (edges) of graph, and** L **represents neighborhood level.**

$\mathscr{C}$	$T(Avg\mathscr{C})$	$T(GRAvg\mathscr{C})$	$T(LRAvg\mathscr{C}_L)$
D	$O(n^2)$	$O(n^2)$	$O(max\{n^2, \lvert N_L(v)\rvert^2\})$
K	$O(mn)$	$O(mn)$	$O(max\{n^2, \lvert N_L(v)\rvert^3\})$
CC	$O(n^2 d_{max}^2)$	$O(n^2 d_{max}^2)$	$O(max\{n^2, \lvert N_L(v)\rvert^4\})$
ASP	$O(n^3)$	$O(n^3)$	$O(max\{n^2, \lvert N_L(v)\rvert^3\})$

that $LRACC(v) = GRACC(v)$, $LRAD(v) = GRAD(v)$, and $LRAK(v) = GRAK(v)$ when L is the diameter of the network.

V. IMPLEMENTATION

This section illustrates six real distinct networks to evaluate the performance of our methods. Later SIR, the Independent cascade model, and Kendall rank correlation are described to analyze the results.

A. DATA

Six real networks are used for simulations such as USAir97, bio-celegans, ca-netscience, web-polblogs, email-univ, and Fb_Pages. These real networks are downloaded from [49]. The basic details of the data sets are summarised in the Table 3. The degree distribution plots for six datasets are shown in Fig. 2. The degree distribution (neighbor distribution) is the most significant characteristic of a network structure.

B. SPREADING MODELS

The SIR (Susceptible-Infected-Recovered) model is one of the epidemic model [50], [51]. To assess the techniques in this report, we apply the SIR model with minimal contact. Each node in the SIR model must be in one of these

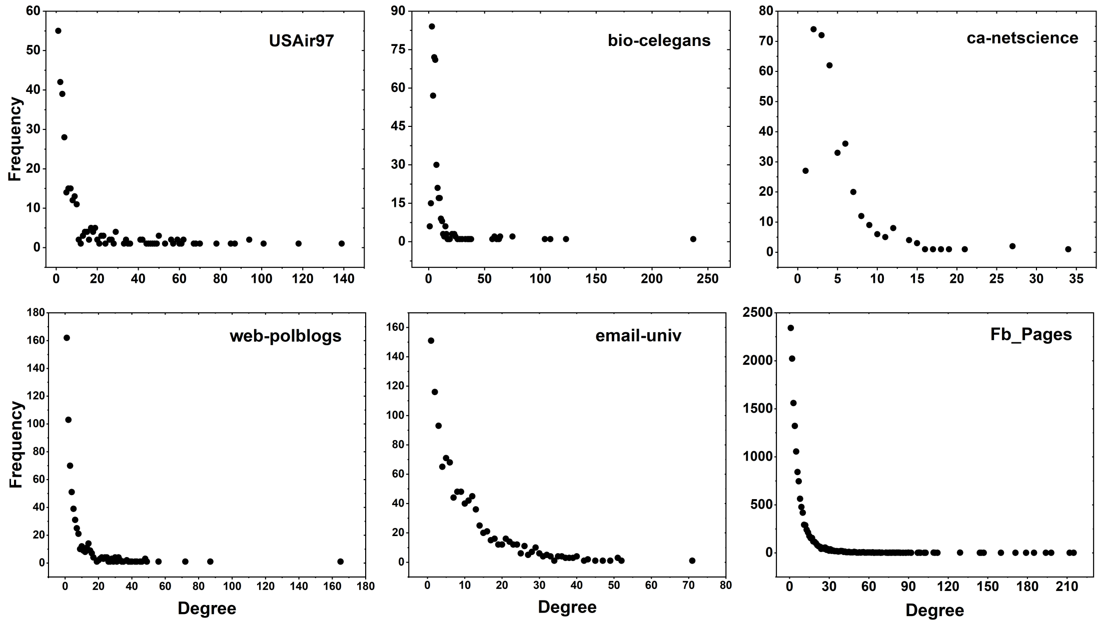

FIGURE 2. Degree distribution for USAir97, bio-celegans, ca-netscience, web-polblogs, email-univ, and Fb_Pages data sets.

TABLE 5. Rank Correlation (τ) values of various (Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global relative change in average clustering coefficient), LRACC (Local relative change in average clustering coefficient), GRAD (Global relative change in average degree), LRAD (Global relative change in average degree), GRAK (Global relative change in average Katz), and LRAK (Local relative change in Katz)) centralities.

Networks	D	B	C	CC	K	PR	LGC	ISC	GRACC	LRACC	GRAD	LRAD	GRAK	LRAK
USAir97	0.002	0.123	0.150	0.118	0.117	0.031	0.093	0.862	0.044	0.045	0.054	0.211	0.240	0.029
bio-celegans	0.070	0.058	0.014	0.003	0.020	0.029	0.018	0.982	0.030	0.116	0.033	0.111	0.007	0.050
ca-netscience	0.233	0.320	0.144	0.180	0.205	0.235	0.226	0.821	0.080	0.175	0.241	0.144	0.099	0.123
web-polblogs	0.154	0.125	0.166	0.151	0.030	0.039	0.052	0.715	0.077	0.108	0.177	0.148	0.060	0.026
email-univ	0.481	0.423	0.520	0.141	0.447	0.389	0.450	0.727	0.053	0.489	0.353	0.486	0.431	0.014
Fb_Pages	0.012	0.010	0.001	0.035	0.007	0.010	0.008	0.777	0.002	0.169	0.022	0.280	0.005	0.002

three states. state of being susceptible (S), infected (I), and recovered (R). For the implementation process, the $top-10$ nodes are picked for infection nodes based on a centrality score. For every time instant, an infected node tries with a chance to infect one of its neighbors with probability β. Simultaneously, there is a high chance of success for every infected node to get recovered with a probability γ, if successful, it will never be infected again and will no longer infect additional susceptible nodes. Further, the completion of the process indicates that the network has no infected nodes. The diffusion process was replicated 100 times in this study. The infection rate β is considered to be in the range of 0.1 to 0.3 for the simulations in the SIR model.

Independent cascade model (IC) is an information diffusion model [52], [53]. The IC model is a dynamical information propagation approach in which data travels through a cascade across the network. Considering the average of a massive number of Monte Carlo simulations the expected spread of a given seed set is computed. Nodes can exist in either an active or passive. (i) Active signifies the already influenced node by the data available in diffusion. (ii) Inactive signifies that the node is entirely ignorant of the information. The IC and SIR models are used to examine our proposed measures.

C. KENDALL COEFFICIENT

It is a rank correlation metric that measures how comparable the data's orderings are when ranked by each of the variables [54], [55], [56]. A similar rank in observations results in a high Kendall correlation among the two variables where as dissimilar rank in observations results in low correlation between two variables. Consider a set of observations $(a_1, b_1), \cdots, (a_n, b_n)$ in which A, B are two random variables and $(x_i), (y_i)$ are unique values. For any observations (a_i, b_i) as well as (a_j, b_j), in which $i < j$ are concordant if both $(a_i > a_j)$ and $(b_i > b_j)$ holds or $(a_i < a_j)$ and $(b_i < b_j)$ holds. Else they are discordant. The Kendall's τ coefficient is computed as $\tau = \frac{N_C - N_D}{\frac{1}{2}(n(n-1))}$, where N_C denotes the total number of concordant pairs and N_D denotes the total number of discordant pairs respectively. The range of coefficients must be within the acceptable range $-1 \leq \tau \leq 1$, for the denominator to be in the total number of possible combinations in the pair. The coefficient is said to have a specific value of 1 if rankings there is a perfection in the agreement among the two ranking

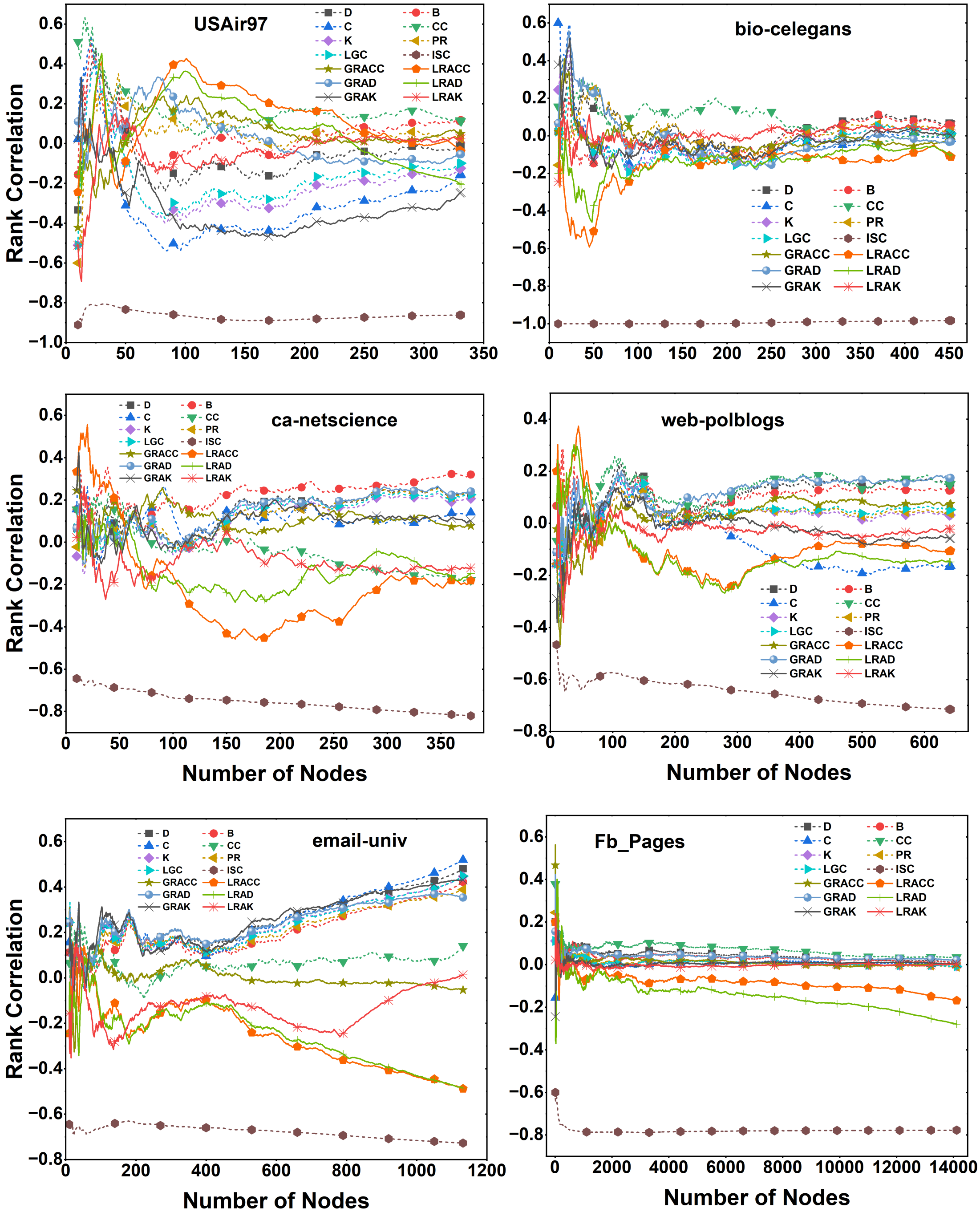

FIGURE 3. Rank Correlation with basic centralities for six data sets. Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz).

whereas the coefficient value is -1 if there is a discrepancy between the two ranks which is perfect. We would anticipate the coefficient to be close to zero if R and S are distinct.

VI. RESULTS AND DISCUSSION

We show the results from various datasets in this section. Initially, we display the correlation between proposed centrality and basic centralities. We explain that the spread of information grows as the centrality of a network node's value rises. We examined cumulative infected nodes for D, B, C, CC, K, PR, LGC, ISC, GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK centralities using the SIR and independent cascade models. For these centralities, we observe the pattern of maximal effect with varying infection rates.

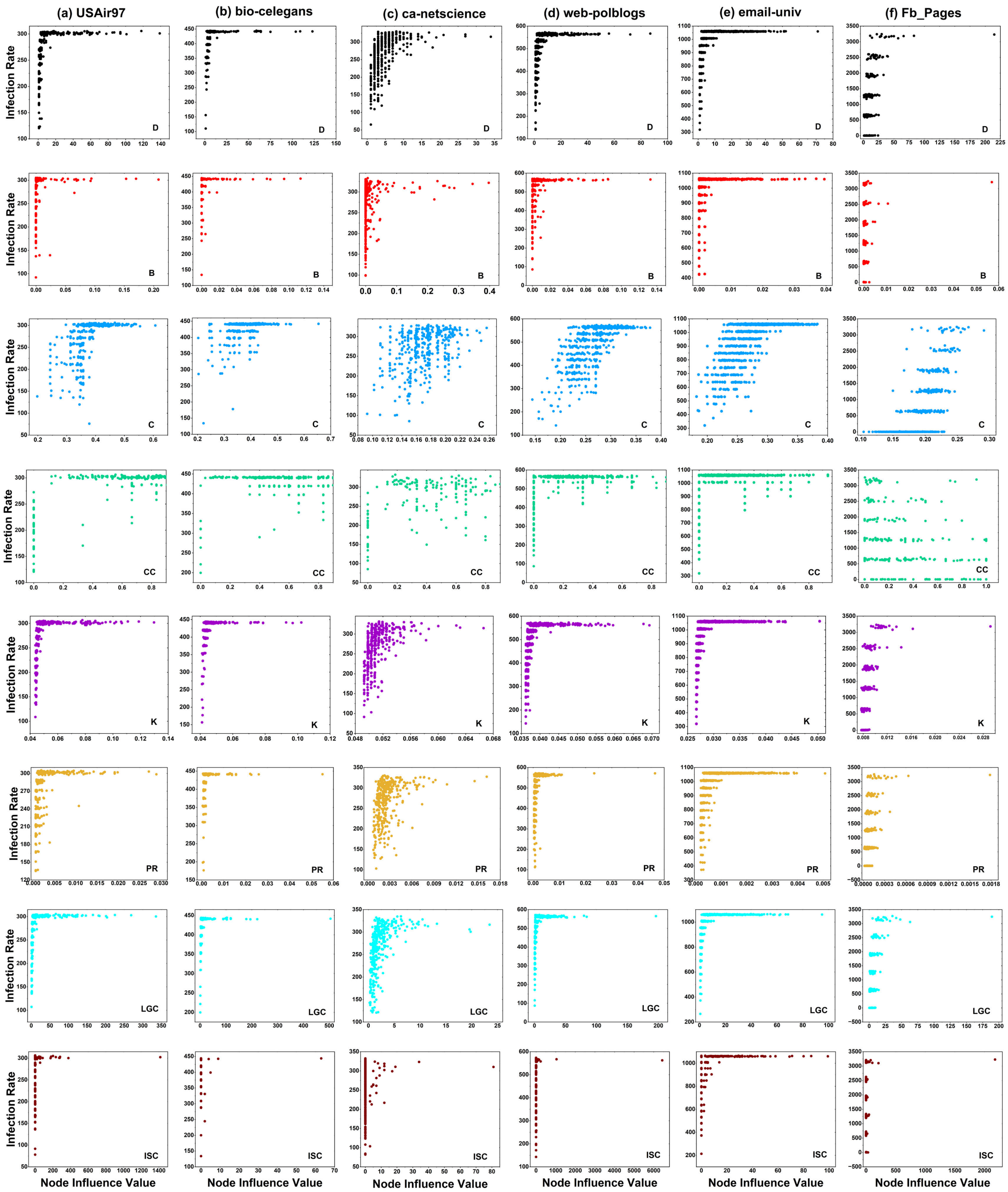

FIGURE 4. Using SIR model, Centrality value with infection rate for six networks in column wise. Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), and ISC (Isolating Centrality).

A. RANK CORRELATION OF GRACC, LRACC, GRAD, LRAD, GRAK, AND LRAK WITH BASIC CENTRALITIES

We define the global and local measures such as GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK in section IV. We investigate the proposed centralities close with any existing centralities by using the Kendall coefficient. On six real networks, we show the correlation of GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK with D, B, C, CC, K, PR, LGC, and ISC centralities. Using the network's centralities, we calculate the ranking of each vertex. For each top N vertices, we provide correlation graphs of the GRACC, LRACC, GRAD, LRAD, GRAK, LRAK with fundamental centrality methods in Fig. 3, here N represents set of values i.e. $N = \{1, 2, \cdots, n\}$ and n denotes total number of nodes in a network. We find correlation between the new rankings (new measures) with basic ranking ($X = 1, 2, 3, \cdots, N$) [38], [57], [58]. Table 5 shows that correlation between new measures and basic centralities for all vertices. In Fig. 3, we show the correlation at every value of x where x is from 1 to the number of vertices of network. In the network,

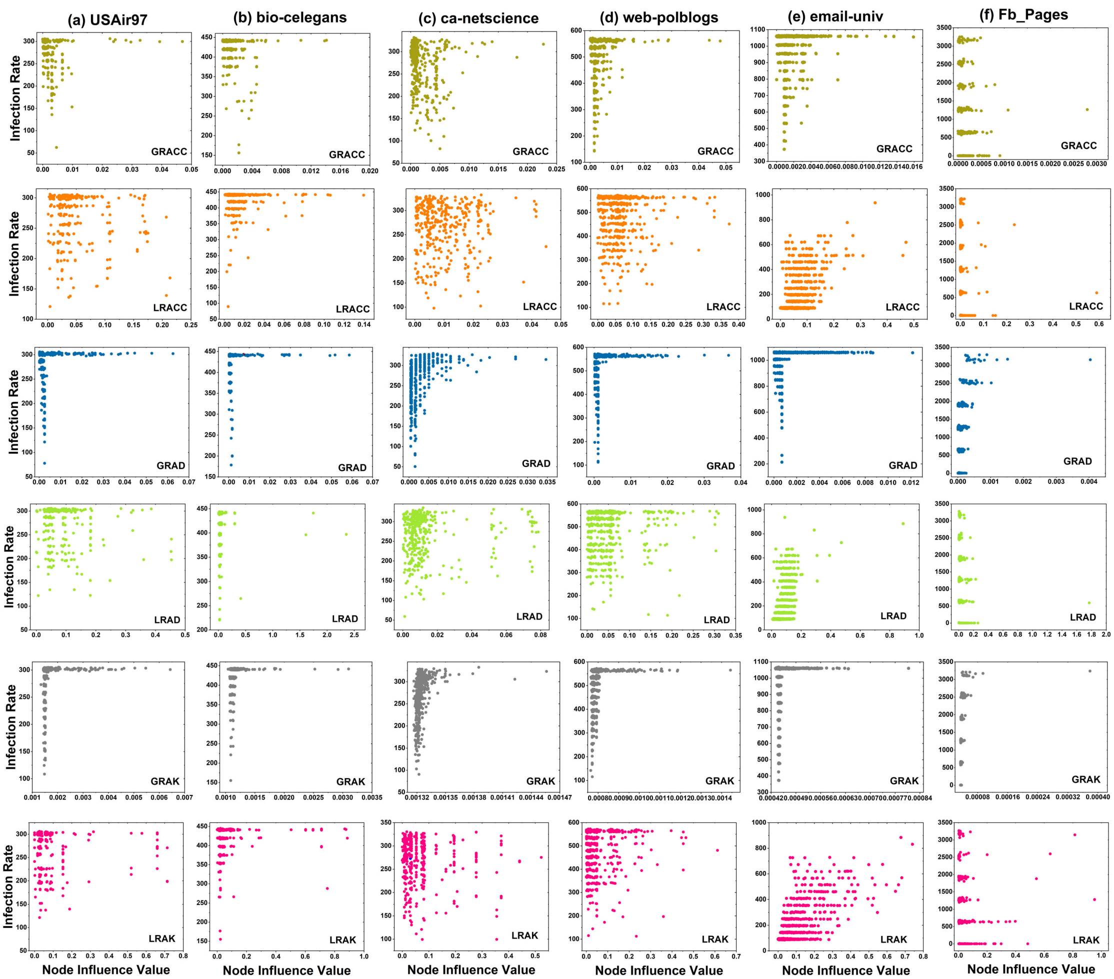

FIGURE 5. Using SIR model, Centrality value with infection rate for six networks in column wise. Where GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz).

we compute rankings of every node by using centrality measures. In USAir97 data set, the correlation between LRACC and LRAD is almost close and LRACC is not correlated with other centralities. In bio-celegans, CC and LRAK, D and B are very closely related respectively. In ca-netscience, B and GRAD are closely correlated. Our proposed centralities (GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK) are not close to basic centralities in web-polblogs, shown in Fig. 3. The proposed centralities' performance is not close to the conventional measures in email-univ and Fb_Pages networks. Initially, GRACC and LRAD centralities are highly correlated with each other. Similar results were observed for GRAK and LRAK centralities. As shown in Fig. 3, other centralities are not correlated in Fb_Pages network.

B. SPREADING ABILITY WITH CENTRALITY VALUE

Considering the count of 100 simulations in the SIR model, we study the relationship between the spread ability and the centrality value of the node in this section. Various centrality methods are assessed for the centrality value of every node. The node with the highest centrality value is considered as an infected node. With 100 times SIR model simulations (described in section V), the total number of infected people is calculated. The infection probability β is set within the range 0.1 to 0.3. If the infection probability goes beyond 0.4, then most of the people in the network will be infected. Using centrality methods such as GRACC, LRACC, GRAD, LRAD, GRAK, LRAK, ISC, LGC, PR, K, CC, C, B, and D, a comparison between the centrality of node's value and the infection rate is graphically plotted. In the Fig. 4, and 5 it is observed that with an increase in infection rate, there is an increase in the centrality value. The experimental results, in Fig. 5(a), show that the proposed methods LRACC, LRAD, and LRAK spread more information compared to other basic centrality methods. More information is being disseminated through GRACC and C centralities. As shown in Fig. 4(b), C, LRACC, and LRAK centralities spread more information than D, B, CC, K, PR, LGC, ISC, GRACC, GRAD, LRAD, GRAK. Later more information is being disseminated through GRAD and GRAK centralities.

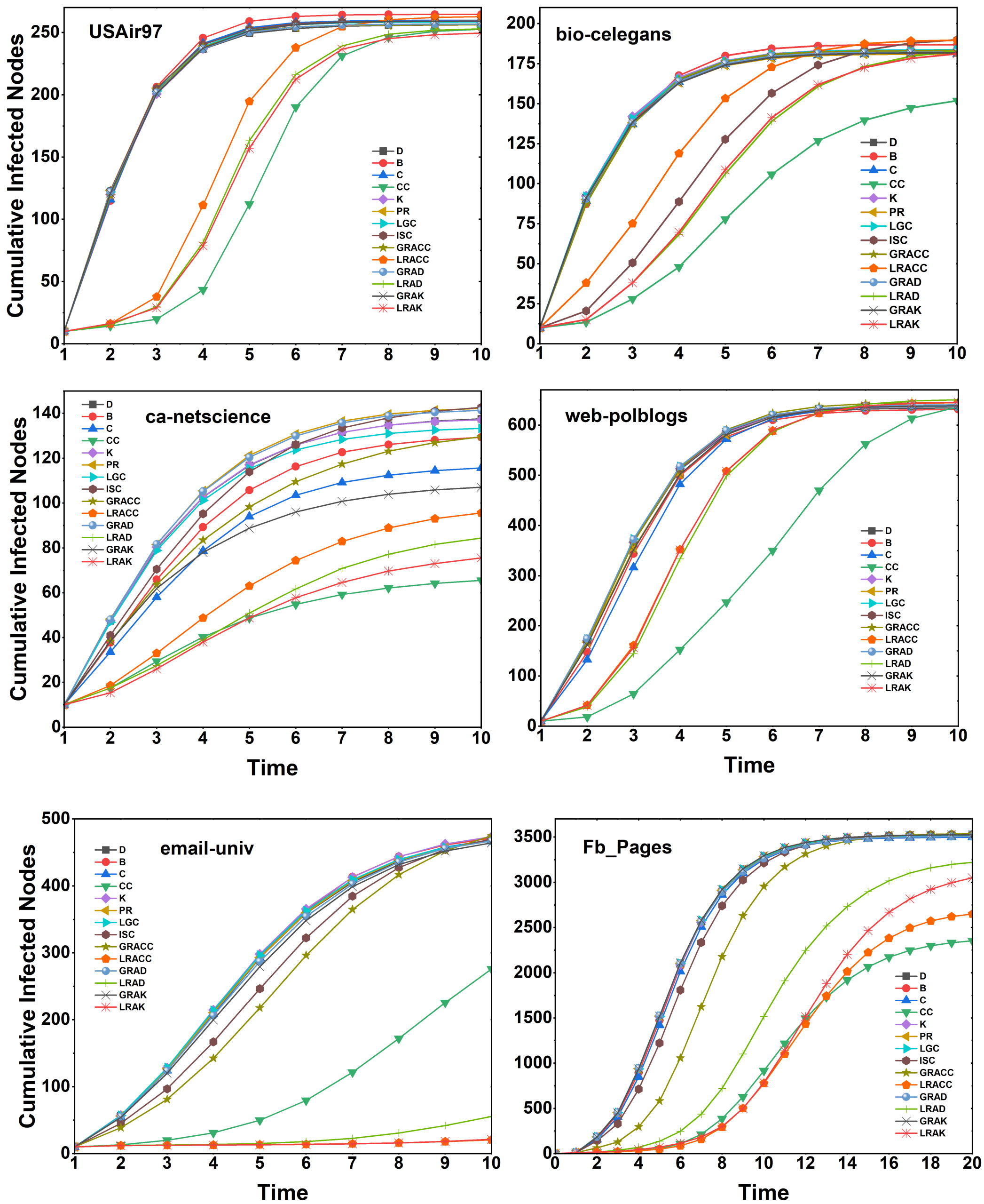

FIGURE 6. 100 simulations of the SIR model's cumulatively infected nodes for the USAir97, bio-celegans, ca-netscience, web-polblogs, email-univ, and Fb_Pages networks. The first 10 nodes listed are infected nodes, as determined by proposed centralities and different centralities.

As shown in Fig. 5(*c*), our proposed local centralities are transforming information more than other centralities. In this dataset, all centralities are transmitting more information except betweenness centrality. In the web-polblogs data set, LRACC, LRAD, and LRAK spread more than other centralities, as shown in Fig. 5(*d*). Later, GRACC and C centralities transmit more information in the network. In Fig. 5(*e*), LRACC and LRAK centrality infection rates are higher. Later C and GRACC have information transmission that is higher than other centralities. The spread of information increases with the node's influence. In the Fb_Pages network, GRAD, LRAK, and C centralities have higher infection rates than other centralities as shown in the Fig. 5(*f*).

C. CUMULATIVE INFECTED NODES FOR GRACC, LRACC, GRAD, LRAD, GRAK, AND LRAK WITH BASIC CENTRALITIES

This section displays the overall infected nodes, as well as the effect of distributing the information after being infected by the *top* − 10 influential (vital nodes) nodes. Using the proposed centrality methods (GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK) and basic centrality methods (D, B, C,

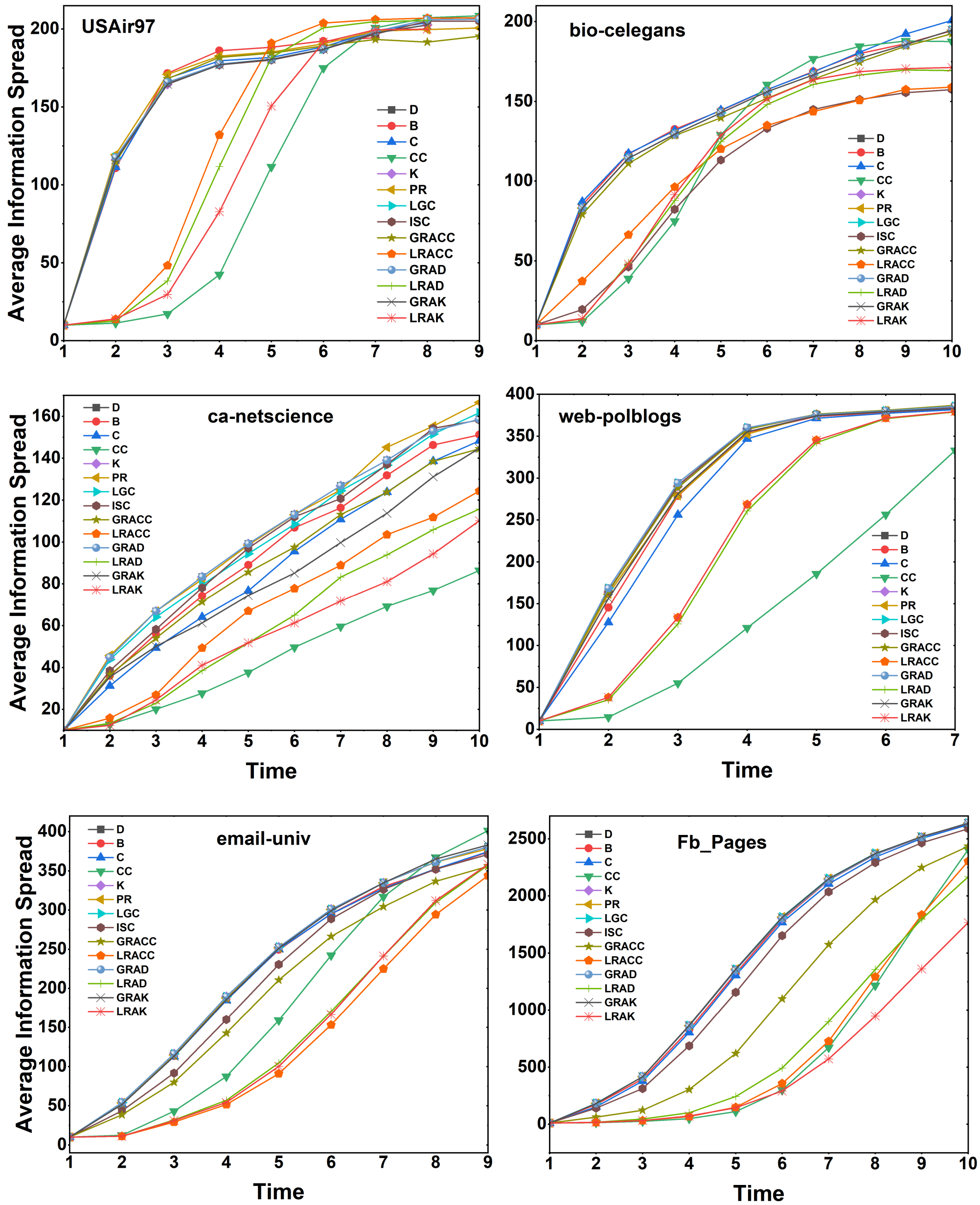

FIGURE 7. Using the independent cascade model (IC model) with *top* − 10 seed nodes, we calculated the average information spread among GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK with other centralities for the six networks Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz).

CC, K, PR), the latest measures (LGC, ISC), the most influential *top* − 10 nodes were calculated. The *top* − 10 vertices which have high centrality are infected initially in the SIR model. In the next stage, the seed nodes of the surrounding/neighboring vertices are infected with infection probability β. The predicted value for infection probability lies within the range of 0.1 to 0.3. Most of the people in the network will be infected if the infection probability goes beyond 0.5. After a certain time period, anyone who becomes infected can be recovered at a specific rate γ, which is defined as 1. The 100 simulations resulted in cumulative infected nodes on an average. We consider the 10 time steps in Fig. 6 which depicts the results. In bio-celegans, ca-netscience, web-polblogs, our proposed centralities LRAD, LRAK, and GRAD all have more spread ability than the other centralities. In the USAir97 data set, the betweenness is performed well and also our centrality LRACC is performed well. Initially, up to some intervals, the degree is performed well. Later, our centrality

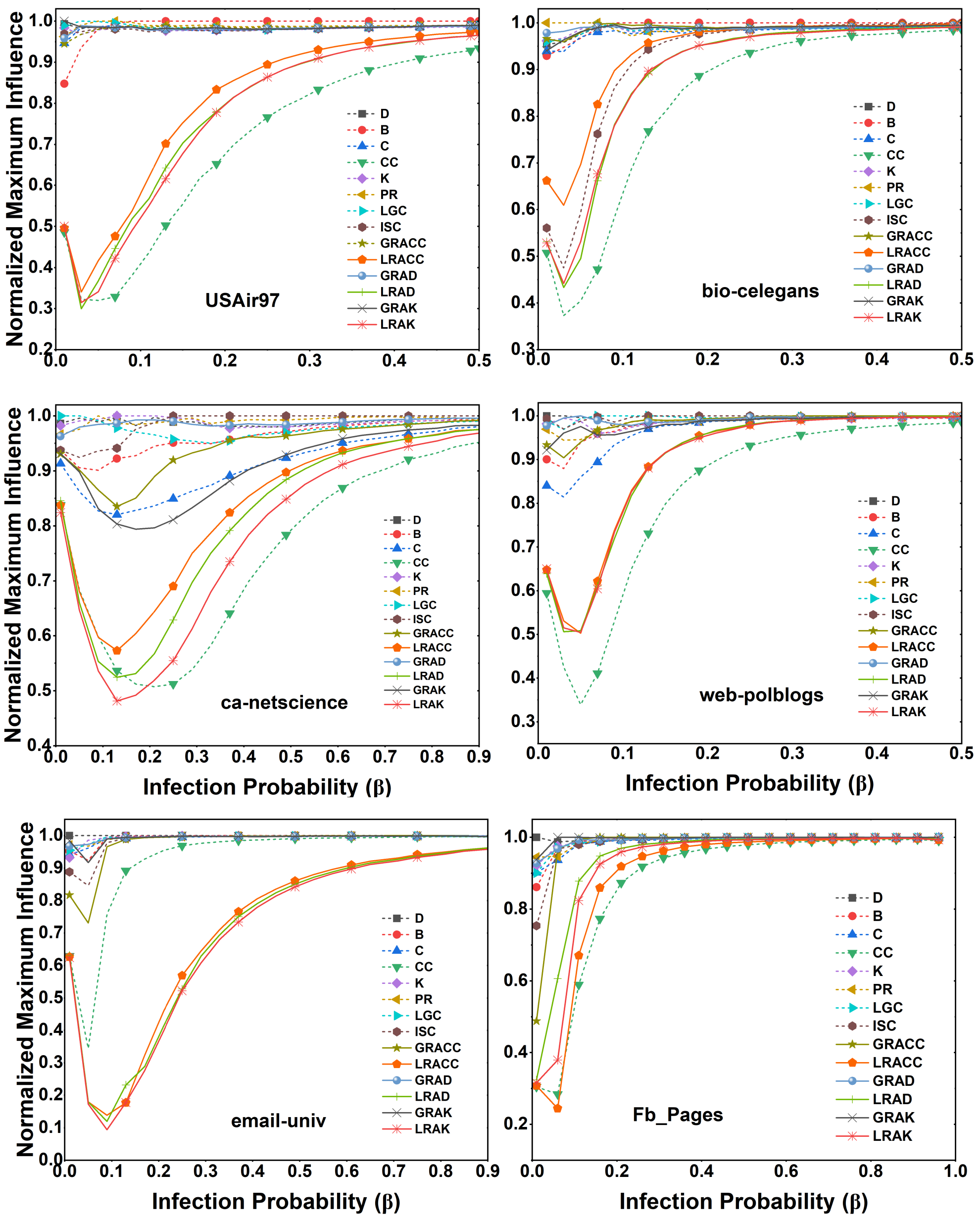

FIGURE 8. Using the SIR simulations, the maximum information spread of the *top* − 10 influenced nodes of networks with varied infection probabilities was normalized. Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz).

measure LRACC reaches the top along with the betweeness. In the bio-celegans data set, LRACC has more spread ability than the other centralities. Later, betweenness centrality also transmits more information, as shown in Fig. 6. GRAD is in top position for spreading information compared to other centralities in web-polblogs. Later, Katz centrality is in the ability to spread more. Our centralities have the ability to spread more in web-polblogs, and some of the basic centralities also have the ability to spread more. GRAD centrality spreading ability is greater when compared with other centralities in the email-univ. GRAK, GRACC, and C centralities spread information faster in Fb_Pages network as shown in the Fig. 6. We have observed a similar phenomenon for the independent cascade method. Using the independent cascade model (IC model), we illustrate the average number of nodes that are information retrieved with different time scales in Fig. 7. Different centrality measurements are used to construct the seed nodes, which are input to IC model. 1000 iterations were employed for simulations in the IC model. In the USAir97 network, the average information spread is more for our proposed methods such as LRACC, and LRAD compared to other centralities. In the bio-celegans network, C, CC,

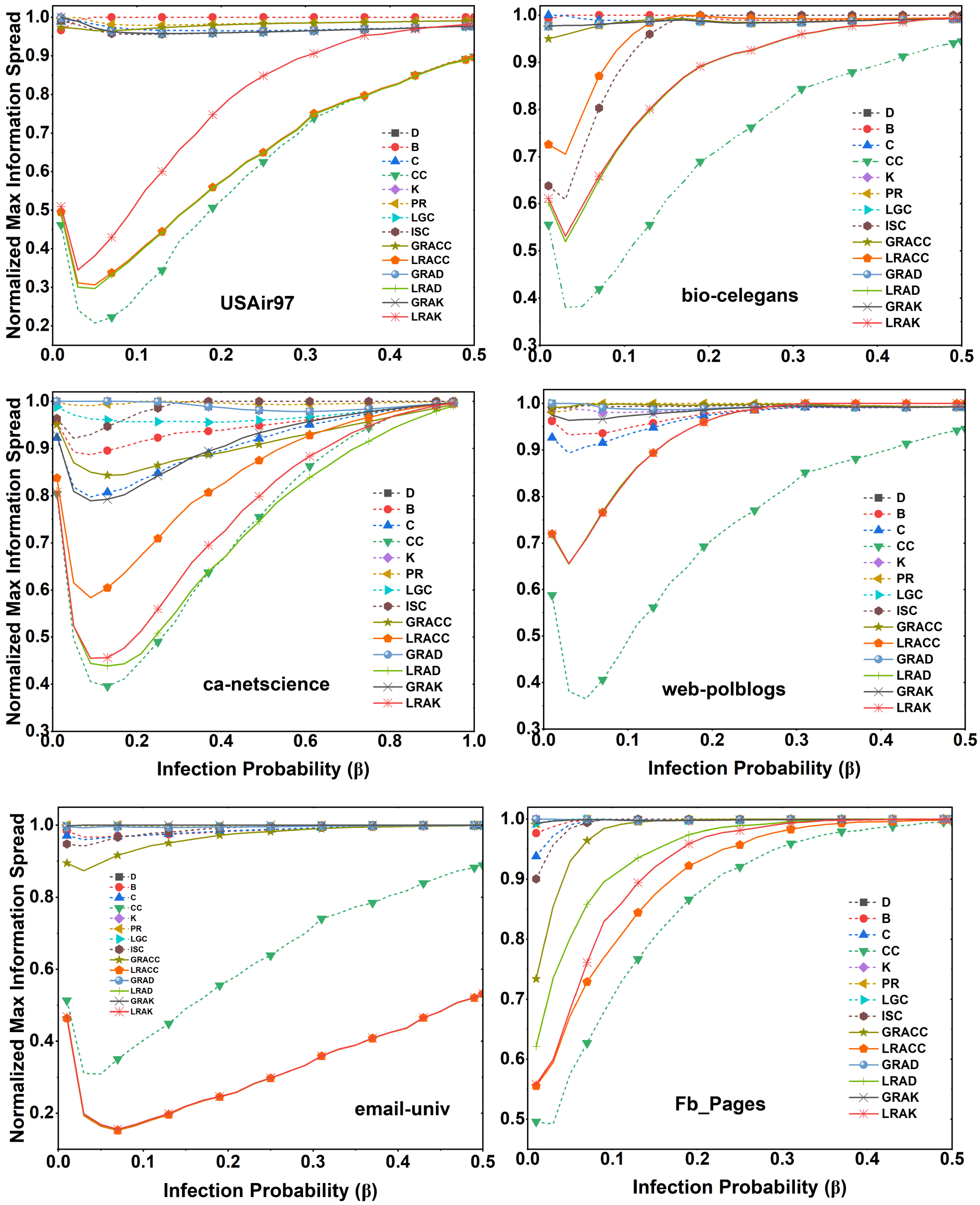

FIGURE 9. Using the independent cascade model (IC model), the maximum information spread of the *top* − 10 influenced nodes of networks with varied infection probabilities was normalized. Where D (Degree), B (Betweenness), C (Closeness), CC (Clustering Coefficient), K (Katz), PR (PageRank), LGC (Local and Global Centrality), ISC (Isolating Centrality), GRACC (Global Relative change in Average Clustering Coefficient), LRACC (Local Relative change in Average Clustering Coefficient), GRAD (Global Relative change in Average Degree), LRAD (Local Relative change in Average Degree), GRAK (Global Relative change in Average Katz), and LRAK (Local Relative change in Average Katz).

and GRAK spread more information than D, B, K, GRACC, LRACC, GRAD, LRAD, and LRAK. The results are shown in Fig. 7. GRAD has a better average information spread than the other methods in the ca-netscience network. GRAD, GRAK, and GRACC have good information spread compared to other centralities in the web-polblogs, the results shown in Fig. 7. In email-univ network, GRAK centrality average information spread is more. As shown in the Fig. 7, GRAK centrality information is more effective over other measures in Fb_Pages network for both SIR and IC models.

D. NORMALIZED MAXIMUM INFLUENCE FOR GRACC, LRACC, GRAD, LRAD, GRAK, AND LRAK WITH BASIC CENTRALITIES

This section displays the assessment of infection spread ability for the top-10 most influential nodes with different infection rate. These nodes are discovered by the D, B, C, CC, K, PR, LGC, ISC, GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK centrality methods. The important nodes have the potential to propagate depending on the information in the networks. Evaluation of infection probability was estimated in the range of 0.1 and 0.5 by using the SIR model (100 simulations). If the infection probability goes beyond 0.5, then most of the people in the network will be infected. When compared with conventional centralities, it was observed that our proposed centrality showed the highest infection population at different levels of infection probability. In this part, we use the IC model to discuss maximum information spread with various infection probabilities (range from 0.1 to 0.3). The results in Fig. 8, show 1000 iterations of IC model simulations. In Fig. 8, we displayed normalized infection (maximum) with different infection probabilities. On the USAir97 network, our methods GRAD, GRAK along with B performed well when evaluated with other centralities. GRAK, GRAD, GRAK, LRAK have highest spread ability than rest of the centralities on the bio-celegans. GRAD, K are positioned top on the ca-netscience data set when compared with rest of the centralities. Similarly GRACC, LRAK are top positioned on the web-polblogs, which are shown in the Fig. 8. As shown in the Fig. 8, faster information spreading is observed for GRAK and GRAD centralities in email-univ and Fb_Pages networks. In Fig. 9, using IC model, we describe maximum information spread with varied probability infection. In the USAir97 network, D and GRACC spread maximum information than B, C, CC, K, LRACC, GRAD, LRAD, GRAK, and LRAK. In the bio-celegans, the LRACC, LRAK, and D centrality methods transfer more information. In the ca-netscience data set, GRAD showed the highest information spread, which is shown in the Fig. 9. In web-polblogs, our centrality methods are at the top, which indicates that information spread is greater. GRAK and GRAD centralities exhibit faster information spread for email-univ and Fb_Pages networks, whereas GRACC centrality shows better performance in Fb_Pages as shown in Fig. 9. Similar observations are clearly seen from both the methods of SIR and IC.

VII. COMPARISON OF PROPOSED CENTRALITIES

In this section, we present the comparative analysis of proposed centrality measures for various real-world data sets. We have tested these measures namely GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK on USAir97, bio-celegans, ca-netscience, web-polblogs, email-univ, and Fb_Pages datasets. We have observed that the performance of GRACC, GRAK, and GRAD measures is good for ca-netscience, email-univ networks, web-polbogs, and Fb_Pages. Similarly, the performance of LRACC, LRAD, and LRAK is better for USAir97 and bio-celegans networks. From the simulation results, we can conclude that the performance of the local and global centralities is highly controlled by the network's structure and properties. It has been also noted that global centralities perform well compared with local centralities for networks with more number of cliques.

VIII. CONCLUSION

In this paper, we proposed six new centrality measures that make use of both local and global structural information. First, we proposed generalized centrality measures based on the relative change of the clustering coefficient, degree, and Katz following node deletion. Then, we demonstrated that the proposed centralities GRACC, LRACC, GRAD, LRAD, GRAK, and LRAK outperformed other centralities such as D, B, C, CC, K, PR, LGC, and ISC. We tested our centrality measures on standard SIR and IC models to ensure maximum information spread. Kendall's tau is used to determine whether the GRACC, LRACC, GRAD, LRAD, GRAK, LRAK, and other existing centralities are equivalent. Furthermore, we demonstrated that our proposed local centrality measures LRACC, LRAD, and LRAK require less computational time. Finally, we demonstrated that the proposed global centrality measures GRACC, GRAD, and GRAK outperform conventional measures in terms of information spread. One of the intriguing future directions is to propose centrality measures that achieve maximum information spread while requiring the least amount of computational time. One of our intuitions is that this can be achieved by combining local and global centrality measures. Furthermore, the relative change of other centralities in the literature can be generalized to investigate the efficacy of current ones.

ABBREVIATIONS

The following are the abbreviations used in this paper:

D: Degree centrality
B: Betweenness centrality
C: Closeness centrality
K: Katz centrality
PR: PageRank
LGC: Local and global centrality
ISC: Isolating centrality
ASP: Average Shortest Path
GRASP: Global Relative change of Average Shortest Path
LRASP: Local Relative change of Average Shortest Path
GRACC: Global Relative change in Average Clustering Coefficient
LRACC: Local Relative change in Average Clustering Coefficient
GRAD: Global Relative change in Average Degree
LRAD: Local Relative change in Average Degree
GRAK: Global Relative change in Average Katz
LRAK: Local Relative change in Average Katz

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