Correlations between Centrality Measures for Mobile Ad hoc Networks

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ABSTRACT

The author conducts an extensive correlation coefficient analysis of four prominent centrality measures for mobile ad hoc networks. The centrality measures considered are the degree-based degree centrality and eigenvector centrality, and the shortest path-based betweenness centrality and closeness centrality. The author evaluates the correlation coefficient between any two of the above four centrality measures as a function of network connectivity and node mobility. He observes a consistent ranking (with respect to the correlation coefficients) among the pairs of centrality measures for all levels of network connectivity, node mobility and across the duration of the simulation session. The shortest path-based closeness centrality measure exhibits high correlation with the degree-based centrality measures, whereas the betweenness centrality exhibits relatively weak correlation with the degree-based centrality measures. For a given level of node mobility and network connectivity, the author does not observe the correlation coefficient values between any two centrality measures to significantly change with time.

Keywords: Centrality, Correlation Coefficient, Mobile Ad hoc Networks, Simulations

1. INTRODUCTION

A mobile ad hoc network (MANET) is a wireless network wherein the nodes move randomly (and often independent of each other) and the topology of the network changes dynamically with time (Murthy & Manoj, 2004). As the nodes operate within a limited transmission range, communication between any two nodes in MANETs is typically through one or more intermediate nodes. Several protocols have been proposed for unicast (Johnson & Maltz, 1996; Perkins & Royer, 1999), multicast (Wu & Tay, 1999; Mnaouer et. al., 2007) and broadcast (Dai & Wu, 2004; Saha et. al., 2010) communication in MANETs. A salient characteristic of these protocols is to optimize one or more performance metrics (relevant to the type of communication being targeted) through appropriate selection of the intermediate nodes that facilitate the communication. The measures typically used to select the intermediate nodes are hop count, node degree, neighborhood density (the sum of degrees of neighbors), residual energy at the nodes, node veloc-

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ity, queue length at the nodes, etc. The design of a MANET communication protocol is typically
done by considering the appropriate node selection measure considered to be directly related to
the performance metric the protocol intends to optimize. For example, shortest path protocols
are designed by choosing intermediate nodes that would minimize the hop count between the
source-destination pair (Johnson & Maltz, 1996; Perkins & Royer, 1999); connected dominating
sets (Cormen et al., 2009) for network-wide broadcasts are determined by choosing nodes with
a larger degree so that the number of constituent nodes for the CDS is as minimum as possible
(to reduce the number of retransmissions) (Meghanathan, 2012; Meghanathan & Dasari, 2013);
a stability-based multicast protocol (Meghanathan et al., 2009) is designed by giving prefer-
tence to go through intermediate nodes that have a relatively lower velocity, etc. Though there
are some works that have analyzed the correlation coefficient between different performance
metrics (for example, the average path duration and throughput in Sadagapan et al., 2003), to
the best of our knowledge, we have not come across any work that has conducted correlation
coefficient analysis between the different node selection measures so that the communication
protocols can choose a related measure in lieu of the commonly used measure in case the two
measures have been observed to have high correlation in a MANET session. In this paper, we
take the first step in this direction by analyzing the correlation coefficient between measures
that are characteristic of the node degree and shortest paths.

Centrality measures are widely used in the analysis of complex networks (Newman, 2010).
However, to the best of our knowledge, centrality measures (other than degree centrality) have
not been used in the design of MANET communication protocols and their analysis. Centrality
measures could be used to rank the importance of a node in the network with respect to one or
more structural characteristics of the network. There could be two broad categories of central-
ity measures: degree-based and shortest path-based. Degree centrality (DegC) and Eigenvector
centrality (EVC) are the two commonly used degree-based centrality measures, while Between-
ness centrality (BWC) and Closeness centrality (CIC) are the two commonly used shortest path-
based centrality measures. The degree centrality of a node is simply the number of neighbors
for the node; the eigenvector centrality of a node is a measure of the degree of the node as well
as the degree of its neighbors. For example, if two nodes u and v have the same degree, but if
the neighbors of u have a relatively higher degree than the neighbors of v, then node u will have
a higher EVC than node v. The betweenness centrality of a node u is a measure of the number
of shortest paths between any two nodes in the network that go through u. Closeness centrality
of a node is a measure of the sum of the number of hops on the shortest paths from the node to
every other node in the network.

Our contribution in this paper is as follows: We let the nodes in a MANET environment
to move according to the well-known Random Waypoint mobility model (Bettstetter et al.,
2004) for a long duration (1000 seconds) with a particular maximum node velocity (v_{max}) and
transmission range (TR) of the nodes. We sample the network regularly and take snapshots of
the network (static graph) at every sampling time instant. We measure the above four centrality
measures (DegC, EVC, BWC and CIC) for the nodes in each of these static graphs and use
the centrality scores of the nodes (with respect to the above measures) to determine correlation
coefficients between any two pairs of the centrality measures (DegC-EVC, DegC-BWC, DegC-
CIC, EVC-BWC, EVC-CIC and BWC-CIC) for every sampling time instant. We analyze the
temporal variations in the correlation coefficient between any two of the centrality measures as
well as measure the time-averaged value of the correlation coefficient. The results of the cor-
relation coefficient analysis indicate that the shortest path-based closeness centrality measure is
highly correlated to the degree centrality and eigenvector centrality measures; on the other hand,
the betweenness centrality measure is weakly correlated to the other three centrality measures.
While the calculations of the shortest path-based centrality measures on a network graph is time consuming, the degree-based centrality measures could be measured relatively more quickly. The results motivate for further research in the design of MANET communication protocols that could use measures such as node degree (measure of degree centrality) and neighborhood density (measure of eigenvector centrality) in the design of shortest path protocols instead of directly attempting to minimize hop count.

The rest of the paper is organized as follows: Section 2 introduces the four centrality measures analyzed in this paper, explains a procedure and an example to determine each of them. Section 3 presents the simulation results obtained for the correlation coefficient analysis between any two centrality measures in a MANET environment. Section 4 concludes the paper. Throughout the paper, the terms ‘node’ and ‘vertex’ as well as ‘link’ and ‘edge’ are used interchangeably. They mean the same.

2. CENTRALITY MEASURES

We now discuss the four centrality measures studied in this paper to quantitatively assess the importance of vertices and the method used to determine each of them, along with an example illustration.

2.1. Degree Centrality

The degree centrality of a node is the number of edges incident on the node. The larger the degree of the node, the higher its rank is. The degree centrality of the vertices is determined by multiplying the adjacency matrix of the network graph with a column vector of 1s, where the number of 1s is the number of vertices in the graph. The adjacency matrix of an undirected graph is a binary symmetric matrix whose entries are indexed with the node IDs. The $i^{th}$ row and $j^{th}$ column of the adjacency matrix is a 1 if there is an edge from vertex $i$ to vertex $j$; otherwise, the entry is a 0. Figure 1 illustrates an example to compute the degree centrality of the vertices. As noticed, the degree centrality measure is likely to lead to tie among one or more vertices and may not be an accurate measure to unambiguously rank the vertices.

If there are $V$ vertices in a graph; there would be $V^2$ entries in the adjacency matrix and the number of multiplications needed to compute the degree of a particular vertex would be $V$. For
$V$ vertices, the total number of multiplications needed would be $V^2$; hence, the time complexity to determine the degree centrality of the vertices in a graph of $V$ vertices is $\Theta(V^2)$.

2.2. Eigenvector Centrality

Eigenvector centrality of a vertex in an undirected graph is a measure of the degree of the vertex as well as the degree of its adjacent vertices. The Eigenvector centrality (EVC) of the vertices in a network graph is the principal eigenvector of the adjacency matrix of the graph. The principal eigenvector has an entry for each of the $n$-vertices of the graph. The larger the value of this entry for a vertex, the higher is its ranking with respect to Eigenvector centrality. We illustrate the use of the Power Iteration method (Strang, 2005) to efficiently calculate the principal eigenvector for the adjacency matrix of a graph (see example in Figure 2). The eigenvector $X_{i+1}$ of a network graph at the end of the $(i+1)^{th}$ iteration is given by:

$$X_{i+1} = \frac{AX_i}{\|AX_i\|},$$

where $\|AX_i\|$ is the normalized value of the product of the adjacency matrix $A$ of a given graph and the tentative eigenvector $X_i$ at the end of iteration $i$. The initial value of $X_i$ is the transpose of $[1, 1, ..., 1]$, a column vector of all 1s, where the number of 1s correspond to the number of vertices in the graph. We continue the iterations until the normalized value $\|AX_i\|$ converges to that of the normalized value $\|AX\|$. The value of the column vector $X_i$ at this juncture is declared the Eigenvector centrality of the graph; the entries corresponding to the individual rows in $X_i$ represent the Eigenvector centrality of the vertices of the graph. The converged normalized value of the Eigenvector is referred to as the Spectral radius. As can be seen in the example of Figure 2, Eigenvector centrality of a vertex is a function of both its degree as well as the degree of its neighbors. For instance, we see that both vertices 2 and 4 have the same degree (3); however, vertex 4 is connected to three vertices that have a high degree (3); whereas vertex 2 is connected to two vertices that have a relatively low degree (of degree 2); hence, the EVC of vertex 4 is larger than that of vertex 2. As can be seen in the example of Figure 2, the Eigenvector centrality values of the vertices are more likely to be distinct and could be a better measure for unambiguously ranking the vertices of a network graph.

The number of iterations needed for the normalized value of the eigenvector to converge is anticipated to be less than or equal to the number of vertices in the graph (Strang, 2005). Each iteration of the power iteration method requires $\Theta(V^2)$ multiplications, where $V$ is the number of vertices in the graph. With a maximum of $V$ iterations expected, the overall time complexity of the algorithm to determine the Eigenvector centrality of the vertices of a graph of $V$ vertices is $\Theta(V^3)$.

2.3. Betweenness Centrality

Betweenness centrality (BWC) is a measure of how significant a node is in facilitating communication between any two nodes in the network. Betweenness centrality for a node is the ratio of the number of shortest paths a node is part of for any source-destination node pair in the network, summed over all possible source-destination pairs that do not involve the particular node. If the number of shortest paths between two nodes $j$ and $k$ that go through node $i$ as the intermediate
Figure 2. Example to Illustrate the Calculation of Eigenvector Centrality using Power Iteration Method

node is denoted as $sp_{jk}(i)$ and the total number of shortest paths between the two nodes $j$ and $k$ is denoted as $sp_{jk}$, then the Betweenness centrality for node $i$ is given by:

$$BWC(i) = \sum_{j \neq k \neq i} \frac{sp_{jk}(i)}{sp_{jk}}.$$

The number of shortest paths from a node $j$ to all other nodes $k$ in an undirected graph can be determined by running the well-known Breadth First Search (BFS) algorithm (Cormen et al., 2009) on the graph, starting from vertex $j$ (which is also considered to be at level 0 for this BFS run). All the vertices that are directly reachable from vertex $j$ are said to be at level 1; the two hop neighbors of vertex $j$ are at level 2 and so on. Though the BFS algorithm primarily determines a shortest path tree rooted at vertex $j$, the level of a vertex $k$ on this BFS tree (i.e., the minimum number of hops from the root $j$ to vertex $k$) can be used to determine the number of shortest paths from the root vertex $j$ to the vertex $k$. The number of shortest paths from the root $j$ (at level 0) to itself is set to be 1. For any other vertex $k$ (at level $l$, where $l > 0$) on this shortest path BFS tree rooted at $j$: the number of shortest paths from $j$ to $k$ ($sp_{jk}$) is the sum of the number of shortest paths from $j$ to each of the neighbors of $k$ (in the original graph) that are at level $l$-1 on the BFS tree.

The number of shortest paths between two nodes $j$ and $k$ that go through node $i$ (i.e., $sp_{jk}(i)$) is simply the maximum of the number of shortest paths from vertex $j$ to $i$ and the number of shortest paths from vertex $k$ to $i$. This can be determined from the BFS trees rooted at vertices $j$.
and $k$ using the approach described earlier. However, the above assertion holds true (i.e., $s_{p_{k}}(i) > 0$) only if node $i$ lies on at least one shortest path between $j$ and $k$. We test this by keeping track of the set of predecessors at all levels ($< l, l > 0$) for a vertex $k$ (at level $l$, $l > 0$) in the BFS tree rooted at vertex $j$ and vice-versa. Accordingly, the set of predecessors for a vertex $k$ at level $l$ in a BFS tree rooted at vertex $j$ is the union of all the neighbor vertices of $k$ (in the original graph) at level $l-1$ in the BFS tree (rooted at $j$) as well as the union of the sets of predecessors of all these neighbor vertices. For an undirected graph, to test whether vertex $i$ is on one of the shortest paths from vertex $j$ to $k$, it is enough to test whether node $i$ is one among the predecessors for vertex $k$ on the BFS tree rooted at vertex $j$. For a graph of $V$ vertices and $E$ edges, we need to run the BFS algorithm once for each vertex. As the time complexity of the BFS algorithm is $\Theta(V+E)$, the overall time complexity of the algorithm to determine the Betweenness centrality of the vertices in a graph of $V$ vertices is $\Theta(V(V+E))$.

Figure 3 illustrates an example to compute the Betweenness centrality of the vertices in the example graph that is also used in Figures 1 and 2. We notice that Betweenness centrality-based ranking of the vertices is different from the Degree centrality and Eigenvector centrality-based ranking of the vertices. The Degree and Eigenvector centralities consider only the degree of the vertices and they are positively correlated. However, the BWC centrality takes into consideration the contribution of a vertex in facilitating communication between any two vertices in the network on the shortest path; such vertices are likely to be more central to the network and form the backbone or the core of the network. As can be seen in the example presented in Figure 3, vertices 2, 4 and 7 all have degree 3 each; however vertices 2 and 7 facilitate shortest path communication between a majority of the vertex pairs, especially from one community (vertices 5, 6 and 8) to another community (vertices 1, 3 and 4). Though vertex 4 has a high degree, it does not lie on the shortest path for several pairs of vertices, and hence has a low BWC value.

### 2.4. Closeness Centrality

Closeness Centrality of a vertex is the inverse of the sum of the shortest path distances to all the other vertices in the graph and hence is a measure of the proximity of the vertex to the rest of the vertices in the graph. Closeness centrality of a vertex is determined by running the BFS algorithm starting from that vertex: sum up the level of every other vertex (the minimum number of hops to reach the vertices) and finally invert the sum. The larger the value of the inverted sum of shortest path distances on the BFS tree of a vertex, the higher is its rank based on Closeness centrality. Figure 4 illustrates an example to compute Closeness centrality. Note that vertices 2, 4 and 7 that lie in the center of the network and have the lowest sum of the shortest path distances (12) to every other vertex (and hence have the largest value for the inverse of the sum) are ranked to have the largest Closeness centrality; though vertices 2 and 7 also had the highest Betweenness centrality, vertex 4 had a lower Betweenness centrality.

For a graph of $V$ vertices and $E$ edges, we run the BFS algorithm once for each vertex to determine the sum of the lengths of the shortest paths from a vertex to every other vertex. With a $\Theta(V+E)$ time complexity for the BFS algorithm, the overall time complexity to compute the Closeness centrality for all the vertices in a graph of $V$ vertices is $\Theta(V(V+E))$.

### 3. SIMULATIONS

We conducted the simulations in a discrete-event simulator implemented in Java. We assume a network of dimensions 1000m x 1000m (area $A$); the number of nodes ($N$) is fixed as 100; if $TR$ is the transmission range of the nodes in the network, then the average number of neighbors per
node is \( \pi^*TR^*N/A \). We vary the network density by conducting simulations with transmission range values of 150m, 250m and 350m corresponding to average number of neighbors per node values of 7, 20 and 38 respectively. Accordingly, we refer to the connectivity of the network to be moderate (about 95% for \( TR = 150m \)), high (99% or above for \( TR = 250m \)) and very high (guaranteed to be 100% for \( TR = 350m \)) for the duration of the simulation session (1000 seconds). The mobility model used for the nodes is the Random Waypoint model that operates

Figure 3. Example to Illustrate the Calculation of Betweenness Centrality

Figure 4. Example to Illustrate the Calculation of Closeness Centrality
with a parameter called the maximum node velocity, \( v_{\text{max}} \). To start with, the nodes are uniformly-randomly distributed throughout the network. Each node moves independent of the other nodes. The mobility profile for a node is generated as follows: the node chooses a random location to move within the network boundary with a velocity that is uniform-randomly chosen from the range \([0...v_{\text{max}}]\) and travels towards the chosen location in a straight line with the chosen velocity. After reaching the targeted location, the node chooses another location and another velocity (from the range \(0...v_{\text{max}}\)) to move; the node continues to move like this for the duration of the session. We repeat the above procedure for every node. We generate a total of 100 mobility profile files for a particular value of \( v_{\text{max}} \). The \( v_{\text{max}} \) values used are: 5 m/s (low mobility), 25 m/s (moderate mobility) and 50 m/s (high mobility).

We sample the network for every 1 second (sampling time period). We take a snapshot of the network for each of these sampling time instants and construct a static graph of the network. There exists an edge between any two nodes in the static graph for a particular time instant if the two nodes are within the transmission range of each other at that time instant. We implemented the procedures described in Section 2 to determine the centrality scores for each of the vertices in the static graph. Using the centrality scores of the nodes at the sampling time instant as the data, we then determine the correlation coefficients between any two centrality measures using the Pearson Correlation Coefficient formula (Strang, 2005) given below, where \( X[i, t] \) and \( Y[i, t] \) are the centrality values, with respect to measures \( X \) and \( Y \), for nodes \( i = 1 \) to \( N \) at time instant \( t \) and \( \bar{X}[t] \) and \( \bar{Y}[t] \) are the average of the centrality values of the nodes at time instant \( t \). We repeat the above procedure for the entire simulation session and determine the correlation coefficients between any two centrality measures for every time instant of the simulation.

\[
\text{Correlation Coefficient } r(X, Y, t) = \frac{\sum_{i=1}^{N} (X[i, t] - \bar{X}[t])(Y[i, t] - \bar{Y}[t])}{\sqrt{\sum_{i=1}^{N} (X[i, t] - \bar{X}[t])^2 \sqrt{\sum_{i=1}^{N} (Y[i, t] - \bar{Y}[t])^2}}
\]

The results reported in Figures 5-7 are the average of the correlation coefficient values obtained (for each sampling time instant) by running the simulations (for 1000 seconds) with the 100 mobility profile files for each combination of the values of \( v_{\text{max}} = 5, 25 \) and 50 m/s and transmission range values of 150m, 250m and 350m. We also compute a weighted average of the correlation coefficient values incurred across all the time instants with the 100 mobility profiles for each combination of \( v_{\text{max}} \) and transmission range values.

We observe a consistent ranking (with respect to the correlation coefficient values) among the pairs of centrality measures for all levels of network connectivity, node mobility and across the duration of the simulation session. The ranking (with respect to decreasing values for the correlation coefficient) is as follows: DegC-EVC, DegC-CIC, EVC-CIC, BWC-CIC, BWC-DegC and BWC-EVC. The time-averaged values shown in the bottom right portion of each of the Figures 5-7 indicate that the correlation coefficient for any two centrality measures does not depend much on the level of node mobility (nevertheless, the correlation coefficient values for any two centrality measures are likely to relatively fluctuate with time in conditions of low node mobility, but average out to a value that is about the same as those obtained for moderate and high node mobility scenarios). For a given level of node mobility, the correlation coefficient values for any two centrality measures is likely to fluctuate with time at moderate network connectivity
Figure 5. Correlation Coefficient Values for any Two Centrality Measures [Low Mobility, \( v_{\text{max}} = 5 \text{ m/s} \)]

Moderate Network Connectivity
[Transmission Range per Node = 150m]

High Network Connectivity
[Transmission Range per Node = 250m]

Very High Network Connectivity
[Transmission Range per Node = 350m]

and remain almost time-invariant when the network connectivity is high and very high. Also, for a given level of node mobility, the correlation coefficient values for any two centrality measures increase with increase in the connectivity of the network and the differences in the correlation coefficient values for various pairs of centrality measures narrows down. In other words, as the

Figure 7. Correlation Coefficient Values for any Two Centrality Measures [High Mobility, \( v_{\text{max}} = 50 \text{ m/s} \)]

Moderate Network Connectivity
[Transmission Range per Node = 150m]

High Network Connectivity
[Transmission Range per Node = 250m]

Very High Network Connectivity
[Transmission Range per Node = 350m]

Time-Averaged Values
number of neighbors per node in the network increases, the centrality measures are more likely to rank nodes in a similar order (i.e., a node having a higher degree centrality is more likely to also have a higher betweenness centrality in networks of very high connectivity and vice-versa).

We observe the shortest path-based closeness centrality measure to be highly correlated to that of the degree-based degree centrality and eigenvector centrality measures. Thus, a high-degree node or a high-degree node in a high-degree neighborhood is more likely to be on the shortest path to the rest of the nodes in the network, compared to a low-degree node and/or a node in a low-degree neighborhood. Such an observation could facilitate us to make an appropriate choice for the root node of a network-wide spanning tree so that a majority of the nodes lie on the shortest path to the root node. Also, this observation indicates to us that data gathering trees for sensor networks (Meghanathan, 2014) rooted at nodes having high degree or high eigenvector centrality are more likely to have a shorter height (lower distance to the other nodes in the network). In a distributed environment, the route selection procedures of shortest path routing protocols could also be tweaked in such a way that if the route request (RREQ) packet encounters a high-degree node on the way and the node knows the shortest path to the targeted destination node, then we can stop the RREQ broadcasts from propagating further and let the high-degree node to respond to the source node of a route to the destination node. If the source node and the high-degree node are either directly connected or few hops away, we could significantly minimize the route discovery overhead without any substantial increase in the hop count of the path from the source to destination.

The betweenness centrality has low correlation with that of the other three centrality measures in networks of moderate connectivity. However, as the connectivity of the networks gets high and very high, the correlation coefficient increases significantly (from values below 0.5 to values close to 0.80 and above). This indicates that in a low-density network of moderate connectivity, a node with high degree need not necessarily lie on the shortest path between any other two nodes in the network (even though a high-degree node is likely to have a shortest path to
Table 1. Summarization of the Correlation Levels for any Two Centrality Measures in MANETs

<table>
<thead>
<tr>
<th>Centrality Pairs</th>
<th>Moderate Connectivity</th>
<th>High Connectivity</th>
<th>Very High Connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>DegC-EVC</td>
<td>High Correlation</td>
<td>High Correlation</td>
<td>High Correlation</td>
</tr>
<tr>
<td>DegC-CIC</td>
<td>High Correlation</td>
<td>High Correlation</td>
<td>High Correlation</td>
</tr>
<tr>
<td>EVC-CIC</td>
<td>Moderate Correlation</td>
<td>High Correlation</td>
<td>High Correlation</td>
</tr>
<tr>
<td>BWC-CIC</td>
<td>Low Correlation</td>
<td>Moderate Correlation</td>
<td>High Correlation</td>
</tr>
<tr>
<td>BWC-DegC</td>
<td>Low Correlation</td>
<td>Moderate Correlation</td>
<td>High Correlation</td>
</tr>
<tr>
<td>BWC-EVC</td>
<td>Low Correlation</td>
<td>Moderate Correlation</td>
<td>High Correlation</td>
</tr>
</tbody>
</table>

the other nodes in the network). Such an observation is very useful for someone who is looking for an appropriate choice for the root nodes of a network-wide spanning trees. If the density of the network is only moderate, a high-degree node may not be an appropriate choice for the root node of a network-wide spanning tree. Instead, a node with a high betweenness centrality (may not be the node with a high degree) would have to be explicitly determined while choosing the root node for spanning trees or data gathering trees. On the other hand, in networks of high and very high connectivity, as the correlation between the degree centrality and betweenness centrality increases and falls within the range of moderate and high-levels of correlation (see Table 1), it would be more apt to choose a node that has a higher degree as well as a higher closeness centrality (no need to compute the betweenness centrality values) to be the root node of network-wide spanning trees and data gathering trees. Note that among the procedures to determine the four centrality measures, the procedure to determine the betweenness centrality is the most time consuming.

Table 1 is a summarization of the results of the correlation coefficient analysis in this research. We use the following cutoff values to define the levels of correlation: 0.80 or above - highly correlated; 0.6 - 0.79 - moderately correlated and less than 0.6 - low correlation. For the connectivity levels of networks, the transmission ranges of 150m, 250m and 350m respectively correspond to networks of moderate, high and very high connectivity. The abbreviations used for the centrality measures are: Degree Centrality (DegC), Eigenvector Centrality (EVC), Betweenness Centrality (BWC) and Closeness Centrality (CIC). With increase in the connectivity of the network (from moderate to high to very high), we see the extent of correlation (if not already high) to increase by one additional level (low to moderate and moderate to high). While the degree centrality and eigenvector centrality exhibit high levels of correlation for all levels of network connectivity, the betweenness centrality and closeness centrality exhibit only low and moderate levels of correlations in networks of moderate and high connectivity respectively.

4. CONCLUSION

The high-level contribution of this paper is a correlation coefficient analysis of the centrality measures (that could be used as the criteria for node selection among the communication protocols) for mobile ad hoc networks (MANETs) whose topology changes dynamically with time. We observe the shortest path-based closeness centrality measure to have high-levels of correlation with the degree centrality measure for even moderately connected networks. As the connectivity of the network increases, the closeness centrality measure becomes further strongly correlated with the degree centrality and eigenvector centrality measures. In networks of very
high connectivity, even the betweenness centrality measure (that showed low correlation with the
degree-based centrality measures in networks of moderate and high connectivity) exhibits high
levels of correlation with the degree-based centrality measures. The results of this research open
up possibilities of designing unicast and multicast routing protocols that take into consideration
the degree of the intermediate nodes as part of the node selection criteria. Also, since the closeness
centrality measure exhibits high-levels of correlation with the degree centrality and eigenvector
centrality measures, the root node or the coordinating node for any network-wide communication
topologies (like shortest path trees, spanning trees, data gathering trees, connected dominating
sets, etc) could be the node with the highest degree or the one that has highest eigenvector central-
ity (as such a root node is likely to be on the shortest path to every other node in the network).
As the computation of the shortest path centrality measures takes significantly more time than
the computation of the node degree, the positive and strong correlation observed between the
closeness centrality and degree centrality measures for all levels of network connectivity is very
encouraging for the design of shortest path communication protocols for MANETs.

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