Centrality Measures To Ascertain Leaders In Wireless Sensor Networks

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Abstract—Wireless Sensor Networks has been attracting various researchers ever since its appreciation for critical applications. The history of research has always been to improve the QoS like coverage, connectivity, network lifetime, latency etc. Due to the random deployment of sensor nodes on the field of observation, few nodes have burdened to take up the responsibility of maintaining a continuous network connectivity. Such nodes are the leader nodes or critical nodes. Identification of such nodes can be of great importance to extent the network lifetime. This paper proposes a unique way of identifying the leaders through centrality measures in the initial deployment phase. The paper concludes to summarise that harmonic-influence centrality identifies leaders more optimally than the betweenness centrality and closeness centrality through experimental setup. The inadequacy of metrics obtained by betweenness and closeness indices are discussed in detail, showing the significance of the harmonic index in leadership recognition across a network.

A. Keywords

Wireless Sensor Networks, Network Reliability, Centrality, Closeness, Betweenness, Harmonic-influence.

I. Introduction

Wireless Sensor Networks (WSN) have always gained interest from the research community due to their sustainability for mission critical applications like disaster management, security, health monitoring, defense networks, battlefield and military exploration, space exploration etc[1]. that require automatic and intelligent interaction with the environment. WSN are either structured or unstructured/ randomized[2][3]. In a structured network, all or some of the sensor nodes are deployed in a pre-planned manner. In an unstructured network, the monitoring area contains dense collection of sensor nodes deployed in ad-hoc manner from UAV (unmanned aerial vehicle). Network maintenance such as managing connectivity and detecting failures is difficult since there are too many nodes. Deployment of sensor nodes in the physical environment may take either of the two forms. Nodes may be deployed at random by dropping them from UAV or can be manually installed at chosen spots. Moreover, deployment may be a one-time activity or an incremental one, where more nodes are deployed at any time during the use of the network (for e.g., to replace failed nodes, to improve coverage at certain interesting locations, to improve the network lifetime, increase connectivity, minimise the latency etc.).

The main objective of any WSN irrespective of the application is to maintain a throughout connectivity thus increasing the network lifetime. Due to the constrained resources available on the sensor node like limited energy, limited storage and processing capabilities, few nodes fail in the due course of action and thus lead to disconnection of the network, if and only if they are the important nodes meant for connectivity. Such nodes are the leader nodes or the critical nodes. Failure of a node does not lead to network partitioning, but failure of a leader node leads to the partition of the network. Prior detection of the leader nodes can advance the phenomenon of partitioning or give an insight for the arrangement of backups. Three different approaches are identified in literature to tolerate the leader node failure viz. proactive, reactive and hybrid. Proactive methods detect the possibility of a leader node failure in an active network, which may lead to network dis-connectivity. Hereon this paper focuses on the proactive approach and the other two are beyond the discussion. Proactive approach is like a precaution taken to identify the leader node before its failure so that necessary action can be triggered on its failure. Network connectivity can be mainly focused at two stages: initial deployment stage and post deployment stage. Due to the ad-hoc placement of nodes, the network may have little or no infrastructure to begin with. Few researchers have taken care to create topology for efficient connectivity at the initial deployment stage[4][5]. This paper also focus on the proactive approach, where the leaders are identified by using the centrality measures. Centrality is used to determine the most influential or important nodes or links within a given network topology. The term ’centrality’ is regarded as a measure of the most important or influential vertices in a graph, and how they influence the neighbouring vertices in a topology.[6]. Popular examples of centrality applications involve ranking influential users in a social graph and identifying the most visited websites.

In connected graphs, *closeness centrality* introduced by Bavelas[7] of a vertex is a measure of the mean distance between itself and every other vertex in an un-directed graph. Closeness may be regarded as the *shortest geodesic* from a given vertex, to every other vertex in a sensor network.

$$C_c(v_\omega) = \frac{1}{\sum_{v_\omega}^{\infty} \delta(v_\omega, u)}$$

where $v_\omega \in V$ is a given vertex and $u \neq v_\omega$. $\delta(v_\omega,u)$ is the geodesic distance between vertices u and v_ω. In order for this definition to be possible, the graph must be *strongly connected* because, if this is not the case then some distances would tend to infinity, resulting in zeroes. Intuitively, the greater the central position of a vertex, the closer it is to all other vertices.

The *betweenness centrality*, proposed by U.Brandes[8] of a vertex v_ω is related with the number of *shortest paths* that a node is involved with. It is the sum of the geodesic paths for vertex-pairs $k,p \neq v_\omega \in V$ that pass through v_ω:

$$C_b = \sum_{k,p \neq v_\omega}^{N} \frac{\delta(k,p|v_\omega)}{\delta(k,p)}$$

The *betweenness* of a vertex is highlighted in [16], [17] as the best measure to discern critical nodes in a given WSN. A major drawback of this measure is its high computational cost and thus, many authors have proposed methods of approximating the measure, presenting a trade-off between accuracy and computational-speed.

This measure of discerning leaders in a WSN is applicable during *information spread* through a network; i.e.- when there is a constant transmission of data between the vertices of a network. However, during the *initial deployment* of a WSN, only the distances between the connected vertices are known, and the betweenness measure is found to be irrelevant. In this paper, the identification of critical nodes at an initial deployment stage is presented, so to optimise the structure of a WSN.

Through careful consideration among different centrality measures, a harmonic influence centrality[9] is chosen as an optimal method for critical recognition in a wireless network during its initial deployment, since only the geodesic between the given nodes holds relevance in identifying central measures. The *harmonic centrality* is obtained by reversing the un-attainability in the definition for closeness[10],

$$C_h = \frac{1}{\sum_{v_\omega \neq u} \delta(v_\omega, u)}$$

This paper is organized as follows. In section II, related work performed by researchers in related fields is explored. Section III formally introduces required background, equations and definitions that will be necessary for the remaining sections. Section IV is concerned with a carefully structured description of our proposed intuition and implementation. In section V, comments and observations on the comparison of centrality indices over a wireless-network are made. Section VI represents a summary of the conclusions that can me made of this work and in section VII, some illustrations and indications for future work that can be carried on are provided.

II. Literature Survey

The identification of nodes that are more influential over a set of nodes has been a key issue in wireless networks. The works in [11] present a theoretical summary of centrality metrics is presented, which neither includes harmonic-influence nor indicates their performance over a wireless sensor network. Different centralised algorithms have been proposed for detecting cut vertices over the recent decade[12][13]. Under these schemes, although every vertex is able to determine a cut in the network, this is usually insufficient because despite the absence of a critical vertex in real-time wireless communications, a source vertex in the disconnected sub-graph may still communicate with other connected nodes.

A BFS-based algorithm for *cut-edge* identification is proposed by B. Milic and M. Malek[14]. It should be noted that this algorithm varies greatly from detection of cut-vertices in connected networks. If a vertex is a critical node, the edges incident on it are not cut-edges and conversely, if an edge that is incident on a vertex is a cut-edge, the vertex cannot be a critical vertex.

Centrality measures in social networks have been studied extensively since the early 20th century to determine various influence and importance measures in society. Bavelas[7] introduced *closeness* for un-directed, connected networks as the reciprocal of the summation of the geodesic distances from a specific vertex to every other vertex which is extended by Lin in his algorithm[15], who optimises this definition so to make it applicable on directed graphs.

Among other popular definitions for centrality, degree centrality, node betweenness and closeness centrality are noted, as reviewed by L. C Freeman[16], as well as the page rank algorithm. These measures have been found useful in a range of applications, including identification of influencers under social networks. However, neither are these measures universally appropriate, nor have they been applied successfully in optimally discerning cut vertices in wireless sensor networks. The frequency of shortest geodesics that a vertex appears on, attributes to its betweenness[17]; it is also evident that the larger the distance between a pair of vertices, the less they tend to influence each other. Under betweenness, the cluster-head could be the most critical node as it is managing the whole network, or a gateway node could act as the most critical node, which may not be toward the center of the network.

Boldi and Vigna in [18] suggest an *axiomatic* approach to study centrality comparatively and describe the application of harmonic centrality measures in social networks. They evaluate the behaviour of centrality measures over changes in size, density and arc-attachments. However, their analogy is restricted to centrality predictions in social networks, and did not include any indications or operations toward critical analysis in wireless sensor networks.

III. Definitions and Equations

This section briefly recalls some notation and a few basic definitions of graph theory that will be used throughout this paper.

A WSN is a un-directed connected graph defined by $S = (V, E, \lambda)$

where V is the set of sensor vertices, and E represents the set of edges between the vertices in V. λ is the transmission range which is same network-wide.

There exists a link between vertices a and b ($a, b \in V$) if and only if they are in operable transmission range of each other.

*Fig.*1 represents an un-directed, connected sensor network with 11 vertices, and 22 communication links.

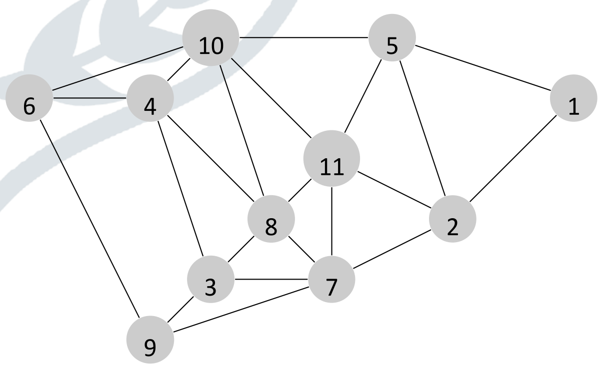

Fig. 1. Connected Network with 11 Sensor Vertices

Connected component of a graph, also referred to *strongly connected* component, is a maximal subset in which there is a path between every respective vertex pair. *Components* are derivatives of *partitioning* the network; thus a graph is *strongly connected* if there is a connected component, that is, for every vertex k, v_ω $v_\omega \in$ V there is a path between k and v_ω.

Closeness of a vertex $v_\omega \in$ V normalised to $N - 1$ with $\delta(v_\omega, k)$ representing the *geodesic* between vertices v_ω and k is defined by

$$C(v_\omega) = (N-1)^{-1} \sum_{v_\omega}^{N} \frac{1}{\delta(v_\omega, k)} \qquad (1)$$

Intuitively, the vertices toward the centre possess considerably larger centrality values. Note that in order for this definition by Bavelas be applicable, the graph must be strongly connected.

The betweenness is defined as

$$B(k \to v_\omega \to p) = \frac{2}{(N-1)*(N-2)} \sum_{k,p \neq v_\omega}^{N} \frac{\delta(k,p|v_\omega)}{\delta(k,p)} \qquad (2)$$

The harmonic-mean is regarded as one of an average metric. It is defined as the reciprocal of the total arithmetic mean in an observation. It is calculated by dividing the number of observations by their reciprocals in the observed set, and is always found to be smaller than the arithmetic mean for a given observation, as it tends to give less relevance to large outliers and more relevance to small values[19]. A definition of the harmonic index for a vertex is obtained as the inverse of the summation of *mean*-harmonic *geodesics* ∀ v_ω ∈ V. This approach, inspired by [18], expresses the harmonic centrality measure for a pair of vertices k and v_ω as the function of the separation between them respectively. In general, this scheme is proposed under social-network analysis and if the harmonic mean for a pair of nodes in wireless networks is to be considered, it is natural to extend this definition to include the euclidean distance between vertices k and v_ω. The harmonic centrality of a

vertex v_ω is obtained as:

$$H(v_\omega) = \sum_{v_\omega \neq k}^{\infty} \frac{1}{\delta(v_\omega, k)} \qquad (3)$$

$$\Rightarrow \sum_{v_\omega \neq k}^{N} \frac{(N-1)^{-1}}{\delta(v_\omega, k)} \qquad (4)$$

where $\delta(v_\omega,k)$ is the euclidean distance between vertices v_ω and k.

IV. Proposed Approach

This section introduces our network model and illustrates relevant approaches that share our intuition and discusses preliminary assumptions for *harmonic-influence centrality* in wireless networks. The network topology consists of varying number of sensor nodes. The sensor nodes are randomly deployed in an 800m x 800m region to construct the network model. Each node is restricted to a 250m transmission range.(λ) The results of averaged over 20 trials whilst simultaneously varying λ between individual experiments.

The simulations were performed on a network simulator, NS2 where λ ranges from 20 to 150m. Assuming strong connection within the network, the observations are discussed.

A. Intuition

This paper proposes a *harmonic* index as a method to ascertain *leaders* (critical nodes) in wireless networks, which is inspired from the works in [18]. Three main axioms for comparatively classifying and categorising centrality indices, based on their behaviour and effectiveness are suggested. A summary of their work is shown in Table I. As suggested,

Index	Size	Density	Arc-attachment
Katz	only k	✓	✓
Betweenness	only p	×	×
Degree	only k	✓	✓
Closeness	×	×	×
Lin	only k	×	×
PageRank	×	✓	✓
Harmonic-influence	✓	✓	✓

TABLE I

only the harmonic-influence index is shown to satisfy all the three axioms and is expressed for a pair of vertices v_ω and k as the function of the distance between respectively.

A comparison for *leadership recognition* across centrality measures is included in this paper. The network is assumed as an un-directed, connected graph and centrality behaviour observations are recorded during the sensor nodes' initial deployment.

$$S = (V,E,\lambda) \text{ and } \lambda = \{20,50,100,150\}, \forall v_\omega \in V$$

Sensor vertices are assumed to operate under equal transmission ranges and constant energy consumption rates.

B. Algorithms

The algorithm proposed for harmonic centrality is mentioned in detail.

Algorithm 1 Input: Un-directed, connected graph $S = [V, E, \lambda]$ with no loops and number of vertices N
Output: List of vertex *harmonic* values

Require: N>1
$norm\_value \leftarrow \frac{1}{N-1}$
$shortest\_path \leftarrow array[N]$
$harmonic\_values \leftarrow array[N]$
for each vertex $v_\omega \in V$ **do**
  $shortest\_path[v_\omega] \leftarrow 0.0$
  $harmonic\_values[v_\omega] \leftarrow 0.0$
end for
for each vertex $v_\omega \in V$ **do**
  $shortest\_path[v_\omega] \leftarrow do\_BFS(v_\omega)$
  for each vertex $w \neq v_\omega \in V$ **do**
    $shortest\_path[v_\omega] \leftarrow shortest\_path[v_\omega] + \lambda$
  end for
  $harmonic\_values[v_\omega] \leftarrow norm\_value * \frac{1}{shortest\_path[v_\omega]}$
end for
return list: *harmonic_values*

V. Observations and Comments

The previous section dealt with algorithm derived from relevant intuitions for a harmonic-centrality index in undirected networks.

This section discusses the observations made by the previously stated algorithm, implemented on a connected, wireless sensor network $S = (V,E,\lambda)$ where V is a set of 100 sensor vertices, $\forall v_\omega \in V$; and E is the link set between the vertex pairs in V and consequently, we get $S = (100,542)$. Fig.2 presents the behaviour of three centrality indices, averaged over 20 trials of individual experiments varying λ values as previously stated, over a wireless sensor network. The graph displays the study of betweenness, closeness and harmonic-influence indices using the previously obtained definitions.

Fig.4 displays the behaviour of the network under the application of our algorithm, over the previously stated network topology. The resulting graph is obtained by normalising colour gradients in harmonic measures for each vertex. A comparison between the behaviour of closeness and harmonic centrality indices in discerning leaders is shown in Table II. $\tilde{h}$ is an *set* of all harmonic values obtained in Fig.2,

$$\tilde{h} = \{ h_0, h_1, h_2,\ldots, h_{99}\} \in [0.0039,0.0181]\forall v \in V$$

$$\tilde{b} = \{ b_0, b_1, b_2,\ldots, b_{99}\} \in [0,0.15907]\forall v \in V$$

Similarly, a range of closeness values is defined as

$$\tilde{c} = \{ c_0, c_1, c_2,\ldots, c_{99}\} \in [0.00452,0.01810]\forall v \in V$$

Notably, although betweenness appears to exhibit the worst behaviour over the network, an important restriction involving the closeness index is also observed; vertices of known tendency further away from the center, are suggested to more likely influence the closeness measure, *suppressing* the contribution of interior nodes; the presence of interior vertices is much more correlated to the *local density* in a network[7]; hence, closeness is bound to behave counter-intuitively, failing to satisfy all three *axioms for centrality*.

Fig.2 displays the ineffectiveness of the closeness and betweenness indices, despite the latter producing mildly correlated results against the harmonic index. For example, the betweenness index ranks vertex 23 to be more influential than vertex 2 as shown in Table II despite the latter bearing greater edge-linkage, and being present in a denser region of the topology. Vertex 23 is edge-connected to 9 other vertices whereas vertex 2 is connected to 18 vertices in the network. In addition, the influence of vertices such as 18 and 19 are ranked

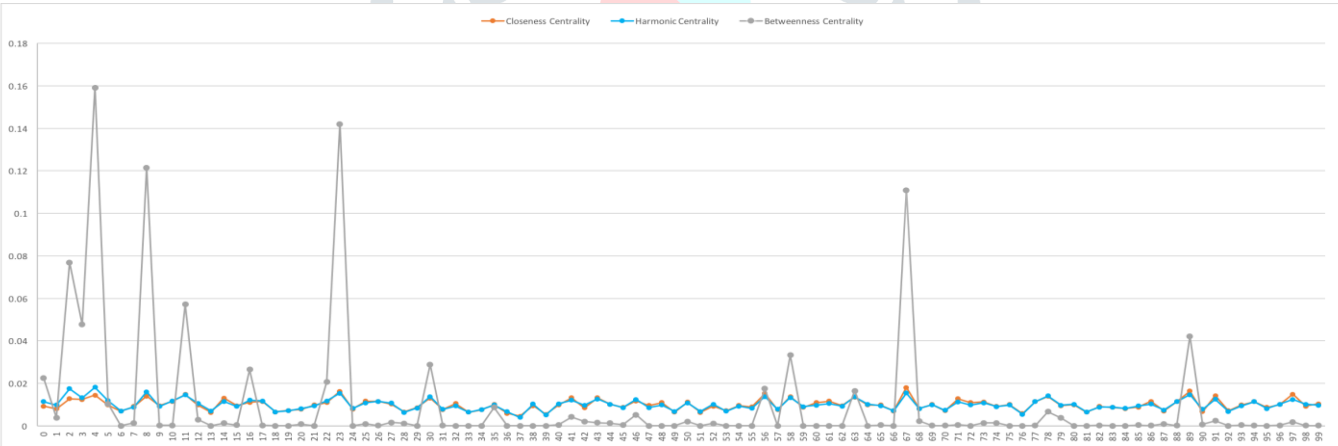

Fig. 2. Comparison of centrality indices on WSN

equally irrelevant(zero-inflated) by betweenness despite the evident rise in the influence value as shown by the harmonic index in Fig.2. The steady rise in the influence values under the harmonic index is not shared by the drop to zero under the betweenness scheme. Similarly, vertices 26 and 38, etc. are ranked as zero-influence while the contrary is shown by harmonic analysis. Evidently, the mutual *influence* between a pair of vertices is inversely affected by the geodesic separation that links them.

A comparative summary of the top 5 leaders, as described by the three indices is shown in Table II. Both *betweenness* and *harmonic* indices recognise the influence of *vertex* 4 as the greatest in the network; It is also determined that closeness is unable to intelligently discern leaders in larger, connected networks.

The infelicity in the results obtained from the betweenness index is discussed briefly. An important intuition in betweenness centrality is that vertices possessing a greater centrality value, appear on more geodesic(shortest) paths in the network. Taking $influence - recognition$ into consideration, it is also evident that the larger the separation between a pair of nodes, the lesser is the *mutual influence* between them[20].

However, a concerning limitation is observed; the betweenness index is shown to perform extremely poorly over large, connected wireless-networks, resulting in $zero-$ *inflated* measures. Another limitation to be noted is the inability of closeness to account for unreachable nodes properly (Fig.3). As the size of the network increases, the influence of the vertices that are distant from the centre cannot be determined precisely; correspondingly *zeros* are obtained,

Index	I	II	III	IV	V
Closeness	67	89	23	56	97
Betweenness	4	23	8	67	2
Harmonic – influence	4	2	8	67	23

TABLE II

Fig.3 and Fig.4 provide a topological indication of *influence recognition* by the closeness and harmonic-influence measures respectively;

VI. CONCLUSIONS

The veracity of three centrality measures, and their precision in discerning leaders in real-time wireless networks is indicated. With regard to recognition of leaders, the paper also describes the application of the *harmonic* index and compares its effectiveness against other centrality metrics. Results tabulated describe the inadequacy in betweenness and closeness indices, bound by certain inherent limitations in their definitions. Evidently, vertex 4 is discerned as the most influential vertex (leader node) with a normalised influence value of 0.018108. The least influential vertex, 37 bears a influence value of 0.0039605.

VII. FUTURE WORK

The future direction of this research can be foreseen as follows; on the one hand, the impact of centrality measures over a wireless network bearing varying energy parameters can be described in more detail. On the other hand, a more rigorous analysis of influence dissemination in wireless networks during its post-deployment stage can be conducted. In addition, the performance metrics over such a topology may be intriguing as areas of research.

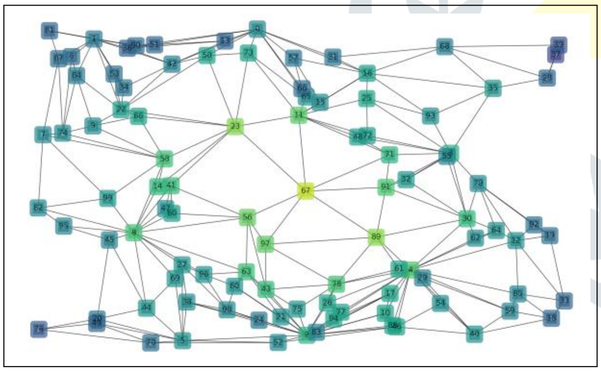

Fig. 3. Behaviour of Closeness in discerning leaders over a WSN

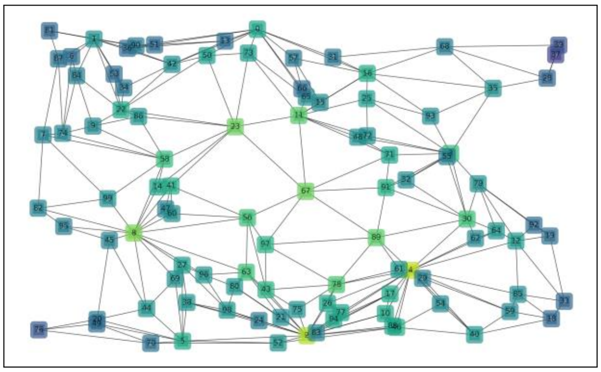

Fig. 4. Behaviour of Harmonic-influence in discerning leaders over a WSN

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