



# Centrality-Based Optimization of a 100-Node Wireless Sensor Network: A Random Walk Model Study

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**ABSTRACT:** This paper aims to refine a specific random walk model of a Wireless Sensor Network (WSN) with a hundred nodes. The optimisation approach uses six centrality measures: degree, betweenness, closeness, eigenvector, Katz, and subgraph centrality, to rank and select nodes to improve communication efficiency, network survivability, and network optimisation. A set of algorithms that determine the importance of a node, known as centrality, is utilized. This study focuses on improving WSN performance by using centrality measures that help in node prioritization. There are also other benefits worth mentioning. Optimizations done at the node level can help yield good traffic flows, as well as network connectivity and network survivability. In addition, our research shows the effect of using centrality in node optimization on scaling and reliability problems that WSNs usually have. The proposed optimization method enhances the WSN functionality, and at the same time, makes important nodes visible and reachable, thus solving a problem that has both academic and industrial relevance.

**Key Words:** Wireless sensor networks, Random Walk Model, centrality measures, network optimization, node ranking, connectivity enhancement.

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## 1. Introduction

The deployment of WSNs includes smart cities, military operations, environmental evaluation, and even health care services. These systems are designed to capture, process, and disseminate information via a network of nodes. In vast and intricate networks, optimization of performance is imperative to network functionality. Meeting operational requirements concerning data flow, fault tolerance, and lifetime of the network poses a challenge [1].

In WSNs, determination of the most prominent nodes is particularly critical. Such nodes are crucial to the operation of the network and its data flow. All centrality measures allow a rank ordering of nodes in one or more networks based on their importance so that chosen nodes can improve system efficiency, robustness, and resilience [2,3,4].

The Random Walk Model has different and new perspectives on WSNs due to its dynamic and stochastic features. It analyzes the random movement of nodes in order to explain a network's evolution and its architectural features. Moreover, this model aids in understanding the data flow within the network, as well as assessing the impact of significant nodes on connectivity and communication effectiveness. Network efficiency can be improved with centrality measures in the Random Walk Model by innovating ways to enhance network survivability. That would maximize the performance of WSNs for several applications.

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## 2. Centrality Measures

In the context of WSNs, determining the significance of nodes becomes an avenue for optimising network performance. Various measures of centrality of importance in the network are a node's degree, links with other nodes and its/rank in the relational tree of the network [5]. The random walk model best illustrates the WSN concept, as it probabilistically captures the information flow within the network. Centrality measures are added to ascertain the relevant nodes that can improve the system's reliability, communication efficiency, fault tolerance, and overall network robustness [6,7,8,9].

### 1. Degree Centrality (DC)

Degree Centrality refers to the number of connections or edges a node has within a network. In WSNs, the hub nodes with a high degree centrality facilitate greater data transmission and improve a node's centrality. However, peak loads may result in heavy congestion, necessitating load balancing to maintain free flow and avoid funnelling. By identifying high-degree nodes, the overall data distribution in the network, along with the effectiveness of the network, substantially improves. The degree centrality of a node  $v_i$  is given by

$$DC = e_i^T A e \quad (2.1)$$

Where,  $A$  is the adjacent matrix of a network,  $e_i$  is the  $i^{th}$  standard basis vector ( $i^{th}$  column of the identity matrix), and  $e$  is the vector of all entries one.

### 2. Betweenness Centrality (BC)

Betweenness Centrality as a concept resonates with a node's capacity to separate different factions of the network by acting as a facilitator of traffic. A pivotal core in device networks characterized by a high betweenness centrality is central to achieving the difficult task of a lengthy communication traversing far-apart nodes. In wireless sensor networks, these nodes are vital for maintaining the connectivity of the network. Their absence may lead to network disintegration alongside other dense traffic on various links. Improving these nodes in a network makes the communication and the entire network system more effective and impressive.

The betweenness centrality of a node  $v$  is given by

$$BC(v) = \sum_{i \neq j} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \quad (2.2)$$

Where  $\sigma_{ij}(v)$  is the number of shortest paths from node  $i$  to node  $j$  passing through  $v$  and  $\sigma_{ij}$  is the number of shortest paths from node  $i$  to node  $j$ .

### 3. Closeness Centrality (CC)

Closeness centrality accepts the shortest path distances as a fact and calculates how a particular node can simultaneously reach the other nodes in the network. Nodes with higher centrality are more proficient in transmissions and, therefore, more likely to relay information of many types. In such wireless sensor networks, these nodes are crucial during many time-sensitive tasks like environment monitoring or communication during critical times in support systems.

The closeness centrality of a node  $i$  is given by

$$CC(i) = \frac{N-1}{e_i^T D e} \quad (2.3)$$

Where  $N$  is the total number of nodes and  $D$  is the distance matrix.

#### 4. Eigenvector Centrality (EVC)

The average quality of links to a network node is defined and quantified through degree centrality. Eigenvector Centrality is an important modification to it. When a node has a high eigenvector centrality, it is linked to other significant nodes in the network. As a result, it is having his/her/its important position in the stability and structural coherence of the network. In the context of wireless sensor networks ( $WSN_s$ ), these nodes provide data flow stability and integrity of the network making them core stabilizers, in addition to being modulators, under varying conditions.

The eigenvector centrality of a node  $i$  is given by

$$EVC = X_i = \frac{1}{\|AX_{i-1}\|} AX_{i-1}, i = 1, 2, \dots \quad (2.4)$$

Where  $X_0$  is the unit column matrix.

#### 5. Katz Centrality (KC)

Katz Centrality may be regarded as an extension of eigenvector centrality which specifies direct, indirect, and multiple dominant links to a node. In WSNs, these nodes assume the roles of network coordinators, facilitating information exchange while maintaining high Katz centrality. These nodes facilitate control and information flow while the interconnectivity and scalability of the network is maintained.

The Katz centrality of a node  $i$  is given by

$$KC = (I - \alpha A)^{-1} e \quad (2.5)$$

Where  $I$  is an identity matrix of order  $n$ ,  $\alpha$  is called the attenuation factor. Here,  $\alpha \in (0, \frac{1}{\lambda})$ ,  $\lambda$  is principal eigenvalue of  $A$ .

#### 6. Subgraph Centrality (SC)

Subgraph Centrality refers to a node's engagement at smaller levels of structure like triangles, clusters or other localities that enhance the connectivity and strength of the node's environment. Such nodes are very important in a region's subnetwork communication, because they actively maintain network connectivity during more extensive network failures. In WSNs, those nodes are responsible for making local data available and are critical in sensor communication systems.

The Subgraph centrality of a node  $i$  is given by

$$SC(i) = \sum_{k=0}^{\infty} \frac{(A^k)_{ii}}{k!} \quad (2.6)$$

This study makes use of these six centralization measures to enhance a One hundred (100) node WSN designed with the Random Walk Model. The objectives are to identify nodes that endorse communication, increase network effectiveness, and enhance network efficiency. The Random Walk approach provides more flexibility than deterministic models because of its stochastically governed movement and interaction between nodes. The application of these centrality metrics is undertaken in hopes of contributing to the understanding of WSNs with the development of a system that is less complicated to manage and functions optimally in a variety of operating environments.

### 3. Results and Discussions

This research focuses on refining a 100 – node Wireless Sensor Network (WSN) via the Random Walk Model with the implementation of six centrality metrics –  $DC$ ,  $BC$ ,  $CC$ ,  $EVC$ ,  $KC$ , and  $SC$ , which de-

termine critical nodes vital for enhancing network function. The network's graphical illustration Fig1 and calculated centrality positions are important indicators of various nodes' functions. The findings

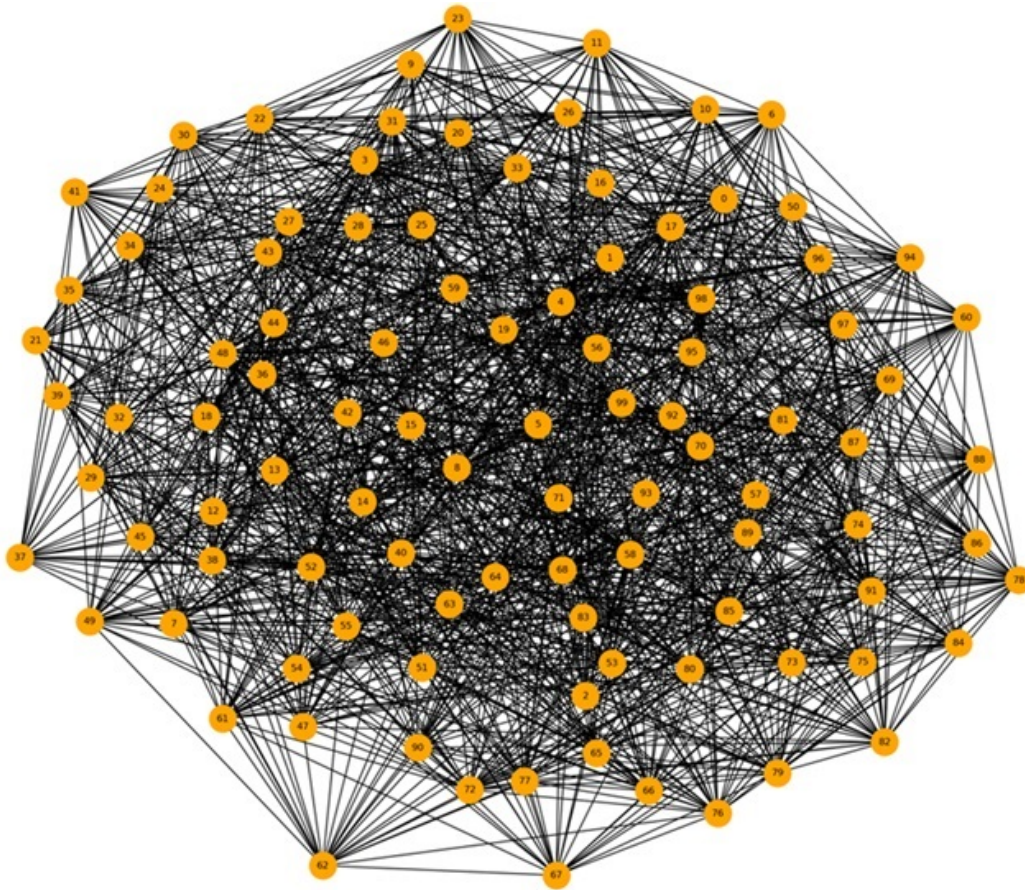


Figure 1: Visual Depiction of a Wireless Sensor Network Consisting of 100 Nodes

suggest that Node 57 has the maximum degree of Centrality, implying that it is the most populated node in the WSN. Consequently, it is critically important for data relay and connectivity. On the other hand, ever-increasing dependence on high-degree nodes is likely to result in network congestion, which calls for effective load-balancing mechanisms.

Further examination indicates that Node 92 has the highest rank in Betweenness Centrality and Closeness Centrality, implying that it acts as an important bridge node. Node 92 functionality as an important intermediate node is evidenced by its high Betweenness Centrality that facilitates communication between various parts of the network. At the same time, its Closeness Centrality attests to the relative speed at which information is relayed across the nodes. This makes Node 92 a vital component in ensuring seamless communication across the network, and any failure at this node may cause significant harm. Also, Node 34 is the most significant in the network structure concerning Eigenvector Centrality and Katz Centrality, indicating her Cognitive Centrality. The strong ties of this node to those of others suggest that this node is crucial for the stability of the network and for making data propagation more effective. The assessment incorporates subgraph centrality, emphasizing Node 57's prominence in constructing micro-scale networks. Nodes possessing a high degree of subgraph centrality are significant for communication at the local level, thereby enhancing the survivability of the network during large-scale failures. The synergy of these centre measures proves that there is no single cut for solving an optimization problem in a WSN; a total view is necessary. Nodes receiving a high degree of betweenness and eigenvector centrality are the most contributory to the system's efficiency and provide an equilibrium between

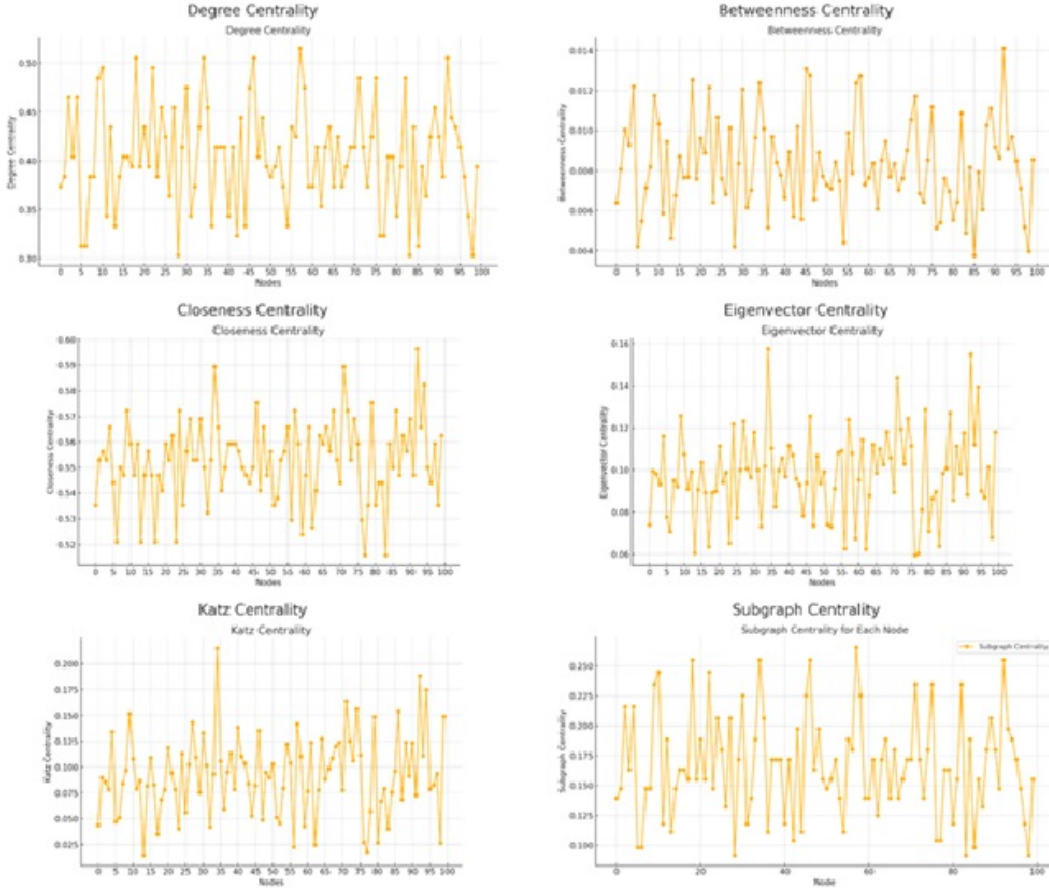


Figure 2: Graphical Representation of Centrality Measures in a 100-Node Network as Shown

system-wide aggregation, local failure immunity, and system performance. These outcomes support the application of centrality-based optimization techniques in enhancing the reliability, scalability, and data transmission efficiency of WSNs [10,11].

Rank	DC	BC	CC	EVC	KC	SC
1	57	92	92	34	34	57
2	18, 34, 46, 92	45	34, 71	92	92	92
3		58		71	94	18, 34, 46
4		46	94	94	71	
5		18	46, 79	79	74	
6	10, 22	34		86	86	10, 22
7		4	9	9	9	
8	9, 71, 75	22	24	46	99	9, 71, 75
9		57	57	57	79	
10		30	68	74	27	

Table 1: Node rankings based on network centrality measures in a 100-Node Network as shown in 1

#### 4. Conclusions

This study develops an optimization framework for a 100-node WSN based on the Random Walk Model, capitalizing on six centrality measures to filter and rank significant nodes concerning network performance. The results show that Node 57 and Node 92 are the most important nodes in the network operation due to Node 57's role as a primary node and Node 92 as an important communicator node. The results also support the claim of the effectiveness of employing more than one centrality measure in node significance evaluation, as different measures evaluate different features of a node's impact. The use of degree, betweenness, closeness, eigenvector, Katz, and subgraph centrality offers the possibility to look at the network from a broader perspective, which helps improve communication efficiency, fault tolerance, and network survivability. When these visions are implemented, the resilience, traffic flow, and data transmission of WSNs are likely to improve. Furthermore, the Random Walk Model guarantees that the network is analyzed dynamically, as nodes are influenced through interaction or movement with other nodes based on specific probabilities. Further research could develop these results by looking into adaptive routing, dynamic reconfiguration, and practical centrality-based optimization in large sensor networks. This study addresses academic and practical aspects by providing a framework for improving the performance and lifetime of WSNs with intelligent node optimization through strategic planning.

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#### 6. Declaration of Interest

The author declares no conflict of interest

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