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Optimizing Wireless Sensor Networks Through Centrality Measures: A Case Study Using the Watts-Strogatz Model

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ABSTRACT

This study provides a comprehensive analysis of Wireless Sensor Networks (WSNs) by applying various centrality measures to identify key nodes within the network. The research focuses on a WSN comprising 100 nodes, modeled using the Watts-Strogatz model. This model effectively captures the network's structural properties, balancing randomness and regularity, which is crucial for understanding real-world WSNs. Degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, Katz centrality, subgraph centrality, and PageRank are utilized to assess individual nodes' relative importance and influence. The analysis highlights the structural significance of specific nodes, particularly those with high centrality scores, which are crucial in optimizing network performance, enhancing resilience, and improving resource management. The results underscore the utility of centrality measures and the Watts-Strogatz model in understanding network dynamics and designing strategies for network optimization, with Node 99 emerging as consistently central across all metrics. These findings have important implications for network management, particularly in applications requiring robust communication and efficient data processing.

Keywords: Wireless Sensor Networks, Centrality Measures, Watts-Strogatz Model, Graph Theory, Network Optimization, Node Ranks.

1. INTRODUCTION

WSNs have emerged as a transformative technology, playing a critical role across a wide range of domains, including environmental monitoring, healthcare, agriculture, and smart cities (Mbiya et al., 2020; Jain and Reddy, 2013). These networks consist of spatially distributed sensors that communicate wirelessly to monitor and gather data on various physical and environmental conditions (Anisi et al., 2011; Jain, 2016). The ability of WSNs to support diverse applications, from tracking climate conditions to enabling remote patient monitoring, highlights their importance in modern technological ecosystems.

The efficient functioning of WSNs depends heavily on the strategic management of key nodes, often referred to as central nodes. These nodes are crucial for optimizing communication paths, aggregating data, and managing the routing of information across the network. The

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performance and reliability of a WSN are significantly influenced by the role of these central nodes, making their identification and analysis essential for effective network management (Gómez, 2019; Landherr et al., 2010).

Identifying these central nodes is a complex but critical task, as they play a pivotal role in enhancing network performance, resilience against failures, and resource management. Central nodes hold strategic positions within the network, directly influencing the robustness and efficiency of data communication. To address this challenge, graph theory offers a powerful analytical framework, enabling researchers to model WSNs as graphs where nodes represent sensor devices and edges correspond to the communication links between them (Pachayappan and Venkatesakumar, 2018; Marsden, 2005). Through this representation, various centrality measures-such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, Katz centrality, subgraph centrality, and PageRank-are employed to assess and quantify the importance and influence of individual nodes within the network (Latora et al., 2017). Each of these measures provides unique insights into the network's structure, identifying nodes that are most connected, those that act as critical intermediaries, and those with significant influence over network dynamics.

To achieve a comprehensive understanding of network dynamics, this study leverages the Watts-Strogatz model-a widely used small-world network model known for its ability to accurately capture the structural properties of complex networks like WSNs (Golbeck, 2015; Latora et al., 2017; Pachayappan and Venkatesakumar, 2018). The Watts-Strogatz model is particularly relevant to WSNs as it effectively balances regularity and randomness, which are key characteristics of real-world WSNs. By starting with a regular ring lattice and introducing randomness through a rewiring probability, the model generates a small-world network with high clustering and short average path lengths. These properties are crucial for WSNs, where high clustering reflects the natural tendency of sensor nodes to form localized communication groups, facilitating efficient data transmission within clusters. The short average path length ensures that information propagates quickly across the network, reducing latency and energy consumption-both critical factors in WSN efficiency. Additionally, the model’s-controlled introduction of randomness mirrors real-world WSN conditions, where environmental factors and energy constraints can influence node connectivity. By applying the Watts-Strogatz model to a 100-node WSN, this study evaluates key node roles using centrality measures, providing insights into network resilience, efficiency, and robustness. These findings are essential for optimizing WSN performance in applications such as disaster response, healthcare monitoring, and smart infrastructure (Golbeck, 2013). By applying various centrality measures to a 100-

node WSN modeled using the Watts-Strogatz framework, this research aims to identify and evaluate the significance of key nodes within the network.

The findings from this analysis will provide valuable insights into optimizing network performance, enhancing resilience, and improving resource management in WSNs. By understanding the roles and significance of these central nodes, network designers can develop strategies that improve the efficiency and robustness of WSNs, particularly in applications requiring reliable and efficient communication, such as disaster response systems, real-time health monitoring, and smart city infrastructure. As WSNs continue to expand and integrate into various critical applications, the ability to effectively manage and optimize these networks will be essential for ensuring their long-term success and sustainability.

2. CENTRALITY MEASURES

Centrality measures in WSNs are crucial metrics that help evaluate the importance or influence of individual nodes within a network. These measures often optimize various aspects of network performance, such as routing efficiency, energy consumption, and network robustness. The key centrality measures used in this study are from Freeman (1977; Ruhnau (2000); Klein (2010); Vázquez-Rodas and Cruz Llopis (2015); Njotto (2018); Zheng and Yang (2021); and Kallakunta and Sreenivas (2024a & b):

2.1. Degree centrality (DC)

Degree centrality is a way to measure how well a node can communicate with other nodes directly (Njotto, 2018; Mbiya et al., 2020). Nodes with a high degree of centrality in WSNs have connections directly to many other nodes. These nodes are important hubs that help disseminate information and connect networks.

$$DC = e_i^T A e \tag{1}$$

Where, A is the adjacency 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.

Degree centrality is used in various fields like social network analysis, biology (e.g., protein-protein interaction networks), and transportation networks to identify highly connected nodes that may be influential or critical to information diffusion or transportation efficiency.

2.2. Betweenness centrality (BC)

Betweenness centrality measures a node's importance in a network by calculating the number of times it appears in the shortest path between all pairs of nodes in a graph (Njotto, 2018; Mbiya et al., 2020). Nodes with high betweenness centrality in WSNs are situated on many shortest paths between other nodes. These nodes play an essential role in information relay and network connectivity. The betweenness centrality of a node *v* is given by

$$BC\ (v)\ = \sum_{i \neq j} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \tag{2}$$

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

Betweenness centrality plays vital in transportation, social, and infrastructure systems. It helps identify nodes that act as intermediaries or bridges, playing a critical role in communication, traffic flow, or information dissemination.

2.3. Closeness centrality (CC)

Closeness centrality determines how quickly a node can reach all other nodes in the network (Njotto, 2018; Mbiya et al., 2020). In WSNs, nodes with high closeness centrality have shorter average path lengths to other nodes, enabling them to disseminate information and coordinate network activities efficiently.

$$CC(i) = \frac{N-1}{e_i^T De} \tag{3}$$

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

Closeness centrality is utilized in transportation, social, and communication networks to identify nodes that can efficiently spread information or resources to the entire network.

2.4. Eigenvector centrality (EVC)

Eigenvector centrality evaluates a node's influence based on its neighbors' influence (Njotto, 2018; Mbiya et al., 2020). In WSNs, nodes with high eigenvector centrality are well connected and connected to other influential nodes. These nodes have a more significant impact on the overall network dynamics.

$$EVC = X_i = \frac{1}{\|AX_{i-1}\|} AX_{i-1}, i = 1,2,3, \dots \tag{4}$$

Where, X_0 is the unit column matrix.

Eigenvector centrality is applied in social networks, recommendation systems, and citation networks to identify nodes connected to other highly important nodes, indicating influence or prestige.

2.5. Katz centrality (KC)

It is a centrality measure that considers direct and indirect paths between nodes in a network (Njotto, 2018). It provides node centrality scores based on the sum of contributions from immediate neighbors and neighbors at increasing distances. Katz centrality can be utilized to evaluate the significance and influence of sensor nodes in wireless sensor networks.

$$KC = (I - \alpha A)^{-1} e \qquad (5)$$

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

Katz centrality is used in social networks, communication networks, and recommendation systems to identify nodes with significant influence, accounting for direct and indirect interactions.

2.6. Subgraph centrality (SC)

Subgraph centrality is a measure of node centrality that considers the structural importance of subgraphs within a network (Njotto, 2018). The sub graph centrality of node *i* in the network is given by

$$SC\ (i) = \ (e^{A})_{ii} \qquad (6)$$

Subgraph centrality is crucial in optimizing wireless sensor networks' performance, reliability, and efficiency across various applications, including environmental monitoring, surveillance, industrial automation, and healthcare.

2.7. PageRank (PR)

PageRank, initially conceived by Larry Page and Sergey Brin, the founders of Google, is an algorithm designed to assess the significance of web pages within search results. It bestows a numerical weight on each component of a linked set of documents, gauging its relative importance in the ensemble. PageRank scrutinizes the interconnections between pages, determining the quantity and quality of links directed toward a specific page. In the realm of WSNs, PageRank can be tailored to gauge the prominence of nodes within the network (Zheng and Yang, 2021). This adaptation proves valuable in scenarios where specific nodes hold pivotal roles in tasks such as information diffusion, data consolidation, or bolstering network steadiness. Implementing PageRank in WSNs opens a spectrum of applications, including pinpointing crucial nodes for functions like data consolidation, routing, and even security (highlighting nodes whose compromise could substantially impact network performance). The PageRank of node v_i in the network with n nodes is given by

$$PR(v_i) = \frac{(1-d)}{n} + d \sum_{j=1}^{n} \frac{PR(v_j)}{N_{v_j}} \qquad (7)$$

In this equation, d denotes the damping factor constrained to the range (0,1). It signifies the likelihood that a user will persist in navigating backward while accessing a specific node at any moment. $v_j (j = 1,2, \dots, n)$ is the node pointing to node v_i; $PR(v_j)$ is the PR value of node v_j pointing to node; and *N* is the number of nodes v_j points to; N_{v_j} represents the number of outgoing links found on node v_j.

In accordance with the PageRank algorithm's computational framework, the significance of node v_i correlates directly with its data transmission volume. Essentially, nodes with higher data transmission rates hold greater importance. Moreover, the importance of node v_i is augmented by nodes that reference or point to it. Consequently, if nodes directing traffic towards v_i are deemed pivotal, then node v_i itself attains greater significance, resulting in a higher PageRank (PR) value for node v_i.

3. RESULTS AND DISCUSSION

Figure 1 presents a graphical representation of a 100-node WSN generated using the Watts-Strogatz model, which effectively captures the small-world properties of the network by balancing randomness with regularity. This model serves as a valuable tool for simulating real-world WSN behaviors. The network structure depicted in figure 1 forms the foundation for applying various centrality measures, essential for assessing the relative importance of nodes and their impact on overall network performance. Figures 2 to 8 illustrate the graphical representation of different centrality values computed for the nodes within the network. Table 1 summarizes the top 10 node rankings within the network, as determined by various centrality metrics.

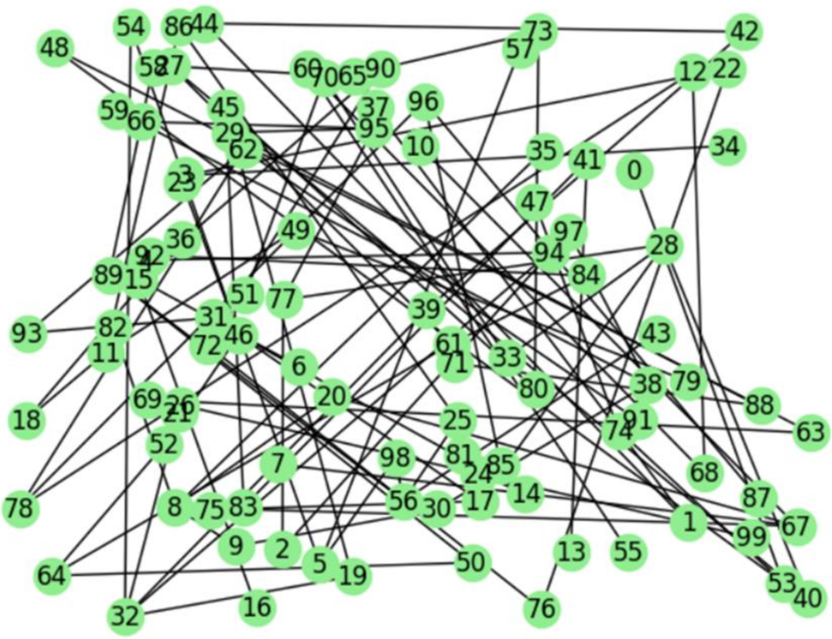

Figure 1. Graphical Representation of a 100-Node Network Generated by the Watts-Strogatz Model.

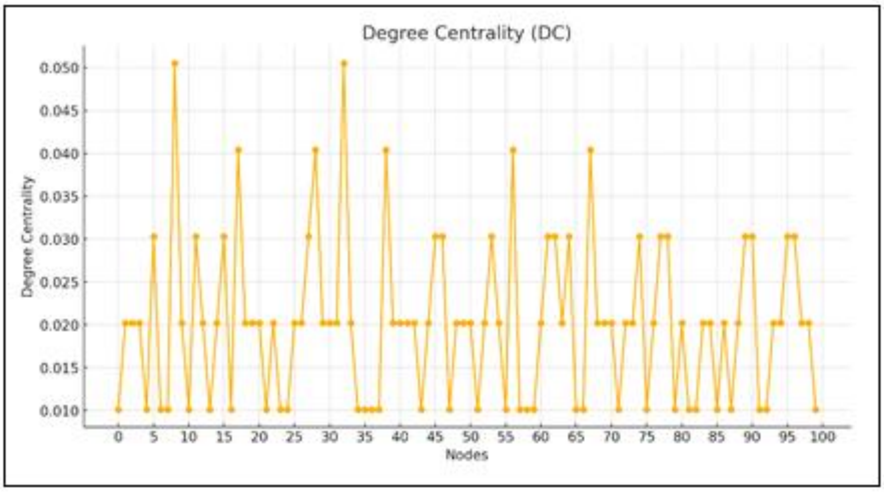

Figure 2. Graphical Representation of Degree Centrality Values.

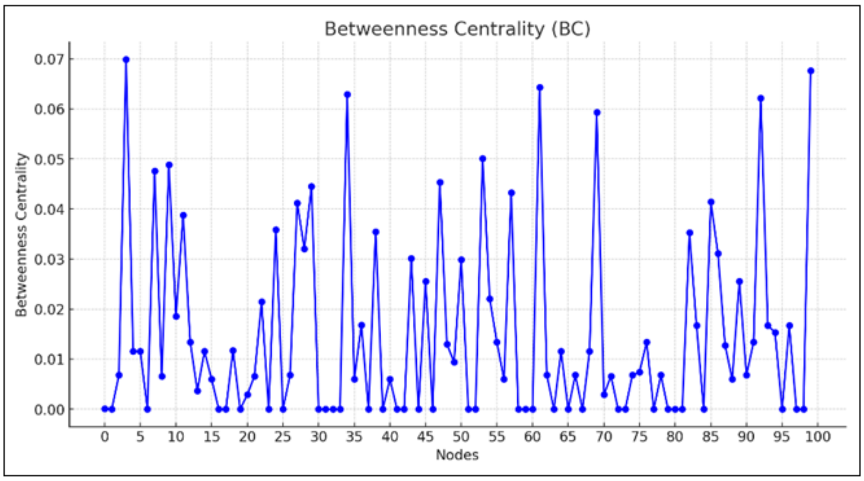

Figure 3. Graphical Representation of Betweenness Centrality Values.

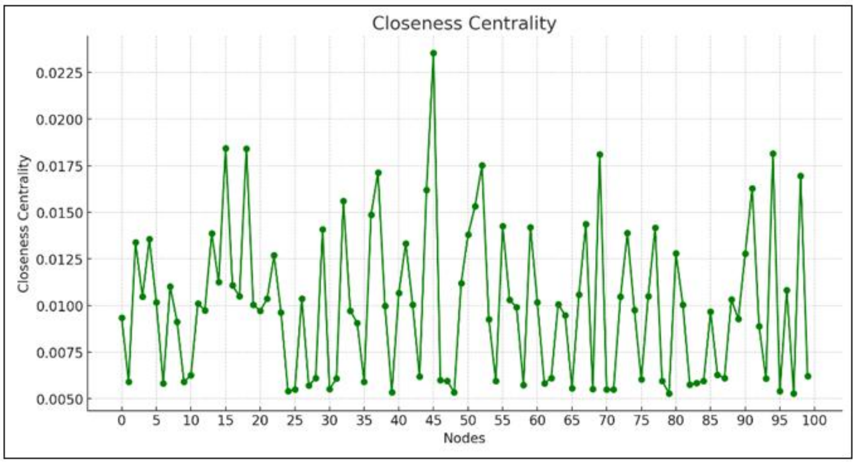

Figure 4. Graphical Representation of Closeness Centrality Values.

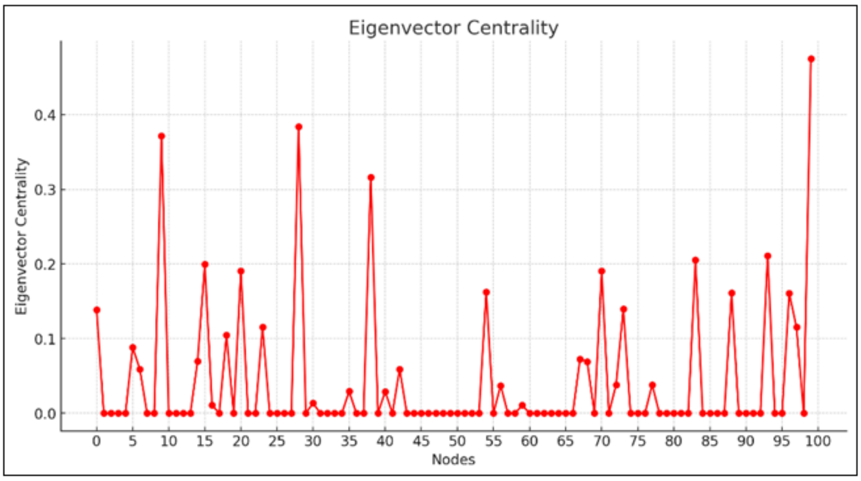

Figure 5. Graphical Representation of Eigenvector Centrality Values.

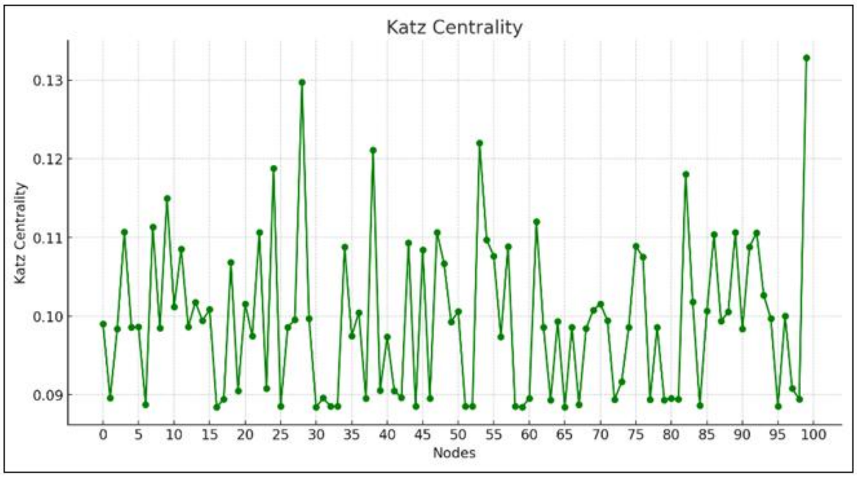

Figure 6. Graphical Representation of Katz Centrality Values.

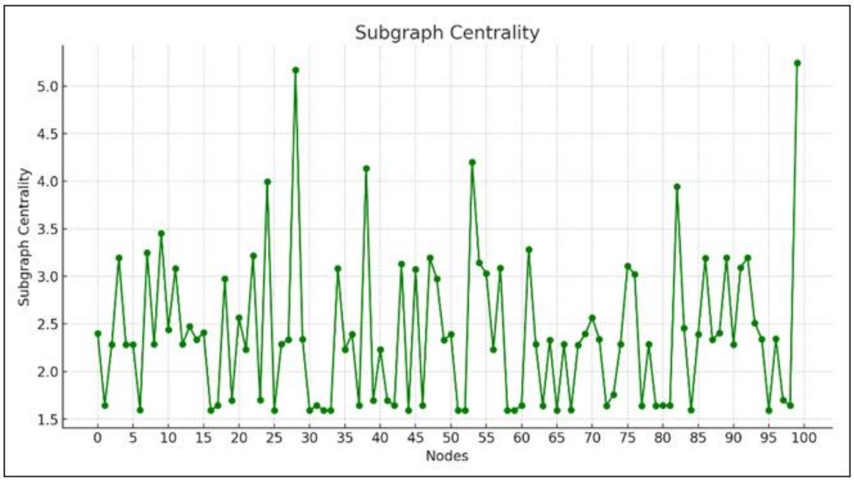

Figure 7. Graphical Representation of Subgraph Centrality Values.

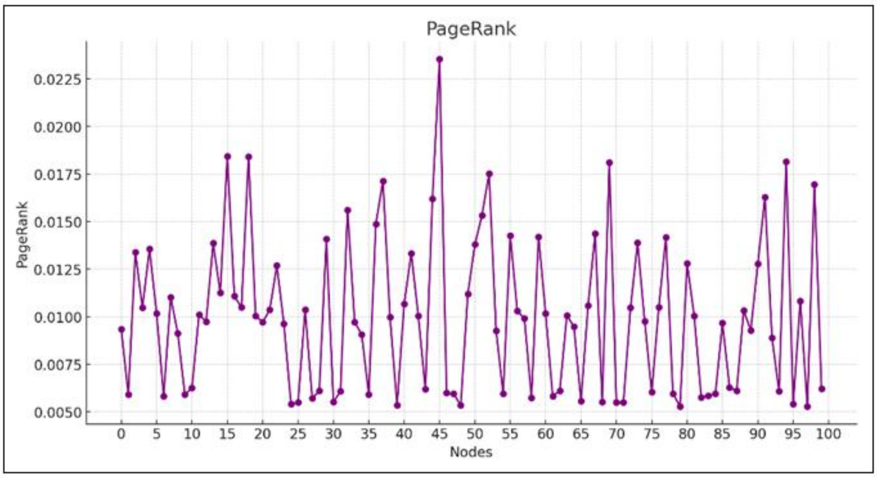

Figure 8. Graphical Representation of PageRank Values.

Table 1. Node Rankings Utilizing Network Centrality Metrics.

Rank	*DC*	*BC*	*CC*	*EVC*	*KC*	*SC*	*PR*
1	8, 32	3	45	99	99	99	45
2	-	99	15	28	28	28	15
3	17,28,38,56,67	61	18	9	53	53	18
4	-	34	94	38	38	38	94
5	-	92	69	93	24	24	69
6	-	69	52	83	82	82	52
7	-	53	37	15	9	9	37
8	45, 46,74	9	98	70,20	61	61	98
9	-	7	91	-	7	7	91
10	-	47	44	54	3	22	44

The analysis of the 100-node Wireless Sensor Network (WSN) modeled using the Watts-Strogatz model provided critical insights into the network's structural properties and the hierarchical significance of individual nodes. Through the application of various centrality measures, the study offers a nuanced understanding of node influence, identifying key nodes essential for the network's overall performance and resilience.

The centrality analysis revealed that Node 45, identified by Degree Centrality, plays a pivotal role as the primary communication hub, crucial for efficient data dissemination and network stability. Node 99 emerged as a central figure in the network, as Betweenness Centrality highlighted its function as a critical intermediary, ensuring connectivity and efficient routing by appearing on numerous shortest paths. Nodes 15 and 18, recognized for their high Closeness Centrality, demonstrated strategic positions for rapid information propagation and minimized communication delays across the network. Node 99's dominance in Eigenvector

Centrality further underscored its influence, not only through its direct connections but also by its association with other influential nodes, significantly affecting overall network dynamics. Katz Centrality reinforced Node 99’s significance, particularly for its combined direct and indirect connections, suggesting its crucial role in both immediate and long-term network operations. Subgraph Centrality also emphasized Node 99's structural importance within localized network substructures, reinforcing its role in maintaining local network integrity and resilience. PageRank analysis corroborated the critical roles of Nodes 45 and 99, especially in scenarios requiring robust data aggregation and dissemination, essential for sustaining network effectiveness.

These findings demonstrate that Node 99 consistently ranks as the most crucial node across multiple centrality measures, highlighting its multifaceted role in the WSN as both a key intermediary and a significant hub. This strategic position strengthens the network’s resilience against potential failures, ensuring robust communication pathways and efficient resource allocation. While Node 45 may not be as universally dominant as Node 99, its high degree and PageRank centrality scores underscore its significant contribution to direct connectivity and data flow within the network. The prominence of Nodes 15, 18, and 28 in specific centrality metrics suggests their vital roles in enhancing network efficiency by facilitating quick communication and maintaining local connectivity.

The use of the Watts-Strogatz model in this study effectively captured the intricate balance between randomness and regularity within the network, enabling a realistic assessment of node importance. The insights derived from this analysis are invaluable for optimizing WSN design, particularly in applications where high reliability and efficiency are paramount, such as disaster response, environmental monitoring, and smart city infrastructure.

4. CONCLUSION

This study provides a comprehensive analysis of a 100-node WSN using various centrality measures within the framework of the Watts-Strogatz model. The application of degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, Katz centrality, subgraph centrality, and PageRank has revealed the hierarchical significance of nodes within the network, particularly highlighting Node 99 as the most influential node across multiple centrality metrics.

Node 99's consistent ranking as the central node across various measures underscores its pivotal role in ensuring robust communication, efficient routing, and overall network resilience. Its prominence is critical in enhancing the network’s performance, especially in scenarios demanding high reliability and rapid information dissemination. Though not universally dominant, nodes such as 45, 15, and 18 play significant roles, particularly in direct connectivity, information propagation, and maintaining network stability.

The insights derived from this centrality analysis are crucial for optimizing WSN design, particularly in applications where efficient resource allocation and robust communication pathways are essential. The Watts-Strogatz model has effectively captured the balance between randomness and regularity, enabling a realistic assessment of network dynamics and providing a reliable foundation for future studies on network optimization.

These findings contribute to the growing knowledge of WSNs and offer practical guidance for network designers to enhance network efficiency, resilience, and performance across various critical applications, including disaster response, environmental monitoring, and smart city infrastructure.

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6. CONFLICT OF INTERESTS

There is no conflict of interests.

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