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Optimizing wireless sensor networks using centrality metrics: a strategic approach

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ABSTRACT

This research paper presents a methodology for improving wireless sensor network (WSN) performance by leveraging centrality measures, including degree, betweenness, closeness, eigenvector, and Katz centrality. Employing a random walk graph model, this study constructs networks with 30 and 50 nodes to investigate the impact of these centrality metrics on routing decisions to optimize energy efficiency, minimize latency, and enhance overall network reliability. Additionally, the paper provides a comprehensive analysis of the relationships among these centrality measures through various correlation techniques, such as Pearson correlation, Kendall rank correlation, and Spearman correlation, offering insights into how these metrics can effectively improve WSN operations.

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1. INTRODUCTION

Wireless sensor networks (WSNs) are advanced, flexible technologies widely used in different fields for effectively monitoring and gathering environmental information. These networks consist of many small, self-operating sensors spread over an area. These sensors return their data to a central location, a sink, or a base station. The collected data is then analysed thoroughly to help make well-informed decisions. The sensors in a WSN can detect a range of environmental factors, like temperature, humidity, movement, pressure, and pollution. After sensing these elements, the nodes process and send the data wirelessly to the central hub. This wireless feature makes WSNs adaptable and suitable for various settings and purposes [1]-[3]. However, running WSNs comes with its own set of challenges. Energy efficiency is one of the most significant issues since the sensors usually run on limited battery life. This has led to developing methods to identify key nodes that save energy and increase the network's life [4]-[6].

WSNs are utilized across diverse fields because they can monitor and collect data remotely. They serve various purposes, including environmental monitoring for tracking climate conditions, soil moisture, and pollution, which is critical for agriculture, forestry, and water management. In healthcare, WSNs enable remote patient monitoring by tracking vital signs and improving patient care outside traditional settings. They are also integral in industrial automation, enhancing efficiency and safety by monitoring machinery and processes. For home automation, these networks contribute to energy efficiency and security by controlling lighting, heating, and surveillance systems. In military applications, WSNs are valuable for surveillance and detecting threats without human risk. They assist in traffic control by managing the flow, detecting incidents, and informing drivers and traffic centers. WSNs are crucial in structural health monitoring, helping prevent disasters by assessing the integrity of buildings and bridges. In agriculture, they optimize irrigation and increase crop yields by monitoring environmental conditions. Furthermore, they are essential in disaster management by providing early warnings for natural disasters and monitoring wildlife by tracking animals and their environments without disturbance, showcasing their extensive applicability and significance in modern technology and daily life [1], [3], [7]-[12].

Given the growing significance and wide-ranging applications of WSNs, this study aims to assess the efficacy of various centrality measures (degree, betweenness, closeness, eigenvector, and Katz centrality) in identifying key nodes. These nodes are characterized by their connectivity and strategic positioning within the network, which is essential for sustaining efficient communication pathways and ensuring the network's overall integrity [13]-[16]. This investigation focuses on reducing computational efforts compared to traditional optimization techniques within networks comprising 30 and 50 nodes. These networks were systematically constructed using a random walk graph model to further elucidate the interrelationships among the centrality measures above. The computational analysis was meticulously conducted utilizing Python programming, providing a robust platform for evaluating the network structures. To rigorously analyze the correlations among the centrality measures, statistical methodologies such as Pearson correlation, Kendall rank correlation, and Spearman correlation were employed. This analytical approach underpins a comprehensive framework for dissecting various structural aspects of WSNs, thereby facilitating an in-depth examination of the significance attributed to each node within these networks.

2. RELATED WORK

The WSNs field has seen significant advancements due to recent research contributions. One notable study by Mbiya *et al.* [6] presents an innovative routing algorithm utilizing centrality measures to optimize data paths within WSNs. This algorithm demonstrates a notable enhancement in network speed, energy efficiency, and fault tolerance compared to the conventional Dijkstra's algorithm. This research underscores the untapped potential of centrality measures in refining routing capabilities in sensor networks, marking a pivotal shift towards more intelligent network management solutions. Delving deeper into network structure optimization, Mazumdar *et al.* [17] examine clustering algorithms used within WSNs. Their research spans various approaches, including probabilistic, deterministic, and fuzzy logic methodologies, focusing on essential elements such as cluster head selection and formation. The findings stress the significance of advanced clustering in extending network life and conserving energy, particularly by addressing the notorious hotspot issue, thereby promoting more sustainable and efficient network architectures. Innovatively, Ahmad *et al.* [18] introduce a novel method employing social network analysis (SNA) for 3D localization within WSNs, utilizing closeness centrality (CC) to enhance accuracy while simultaneously reducing energy demands. This approach, which eliminates the need for node synchronization, signifies a significant leap in localization strategies, offering a blueprint for future high-accuracy, low-energy demand solutions. Bloch *et al.* [19] investigation into centrality measures provides a detailed taxonomy and evaluation of various metrics, such as degree, closeness, and betweenness centrality (BC). Their comprehensive study sheds light on the practical application of these metrics in different contexts, reinforcing that proper selection of centrality measures can significantly impact the analysis and understanding of varied network types. The critical review by Sambo *et al.* [20] on optimized clustering algorithms underlines the integration of machine learning and computational intelligence to mitigate challenges such as energy consumption and network scalability. This meticulous evaluation guides researchers in selecting and implementing the most appropriate clustering strategies tailored to meet the specific needs of large WSNs. Exploring efficiency in network structure, Aditya *et al.* [21] propose a cutting-edge algorithm for cluster head selection based on CC.

This approach drastically improves network efficiency by enhancing energy usage and extending network lifespan, pivotal for maintaining seamless communication across extensive WSNs. The innovative CS-HiBet method discussed by Mahyar *et al.* [22], utilizing compressive sensing to identify nodes with high BC, presents an effective solution for key node detection in large-scale and undefined networks. This technique significantly improves traditional methods by optimizing the accuracy and efficiency of node identification without a complete understanding of the network's topology. In the computational domain, Tuzcu and Arslan [23] explore the efficiency of centrality computations within diverse network environments. Their algorithm demonstrates versatility across different network sizes and settings, suggesting a transformative approach to calculating BC that could benefit various sectors. The studies by Ghanem *et al.* [24] and Shao *et al.* [25] delve into the dynamics of centrality metrics, examining their applications and correlations in evolving network scenarios. These investigations reveal the intricacies of centrality metrics and their adaptability, offering new perspectives on network analysis and the interconnectivity between different centrality measures. Lastly, the energy-aware routing strategy by

Li and Guan [26], leveraging local BC, addresses the paramount need for energy efficiency in WSNs. This approach represents a significant advancement over conventional routing techniques, promising enhanced network sustainability and longevity [26].

Collectively, these studies have significantly advanced WSNs, introducing routing algorithms that improve upon traditional methods in speed, energy efficiency, and fault tolerance using centrality measures. Further research has optimized network structures through advanced clustering techniques and employed social network analysis for more efficient 3D localization. These new ideas, along with others like compressive sensing for finding key nodes and energy-aware routing strategies, show how WSNs are changing, focusing on making them more efficient, environmentally friendly, and easier to manage.

3. METHOD: STRATEGIC NODE IDENTIFICATION IN WSNs

Identifying key nodes in WSNs using centrality involves several steps. First, construct the network graph: create a graphical representation of the WSN. This graph denotes each sensor as a node and each connection between sensors as an edge. This visual representation will serve as the basis for further analysis. Second, calculate centrality measures: for each node in the graph, compute key centrality measures. These measures help quantify the relative importance of each sensor node within the network. Third, rank the nodes: organize the sensor nodes in descending order based on their calculated centrality scores. Higher scores typically indicate a node's more significant influence within the network, highlighting those crucial for maintaining network communication and integrity. Fourth, consider energy constraints (optional): integrate energy efficiency considerations into the identification process. While nodes with high centrality are prime candidates for key roles, their energy consumption should be carefully managed. Evaluate the energy reserves and consumption patterns to ensure these influential nodes do not quickly exhaust their power, compromising network functionality. Finally, analyze the results: carefully examine and interpret the centrality data and energy considerations to pinpoint the most influential nodes within the WSN. Understanding these key nodes helps make informed network management, optimization, and maintenance decisions for enhanced performance and sustainability.

4. CENTRALITY MEASURES IN WIRELESS SENSOR NETWORKS

In this study, centrality methods in graph theory are used to identify key vertices. These methods include degree, betweenness, closeness, eigenvector, and Katz centrality [6], [7], [27]-[39]. They help in understanding the important role of each vertex in the network.

4.1. Degree centrality

Degree centrality (DC) is an essential metric for evaluating the ability of a node to establish direct communication connections within a network. Nodes with a high DC in WSNs possess direct connections. These nodes act as central hubs, enabling efficient information dissemination and establishing essential connections throughout the network. These nodes, located in central positions, have a crucial function in real-time applications by facilitating fast and dependable data transmission. This is particularly important for activities such as monitoring and emergency response. Moreover, their central position optimizes the stability of the network by offering alternative routes in the case of node or link failures. The ability to adjust and respond to changes in real-time enables continuous data transfer even in the event of unexpected interruptions, thereby improving the ability of networks with highly influential and interconnected nodes to withstand faults and recover quickly. The DC of a node v_i is given by:

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

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.

4.2. Betweenness centrality

BC is an important measure that evaluates the importance of a node in a network by quantifying the frequency with which it appears on the shortest paths between other nodes. Nodes with high BC in WSNs strategically position themselves along multiple critical paths, pivotal in transmitting information and maintaining network connectivity. These nodes serve as crucial intermediaries, effectively directing and distributing data across the network, ensuring quick and reliable transmission. High BC nodes are essential in military surveillance and disaster management applications, where rapid data transfer is essential. Moreover, these nodes enhance network resilience and fault tolerance by dynamically adjusting to redirect information in the event of failures, strengthening the network's ability to withstand unexpected challenges. The BC 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*.

4.3. Closeness centrality

CC is an essential metric to measure the efficiency of a node in quickly establishing connections with all other nodes in a network. Nodes with high CC in WSNs have shorter average path lengths to other nodes, making them efficient for distributing information and coordinating the network effectively. Nodes with high CC are essential in quickening the transfer of information within the network, enabling quick data exchange for efficient communication. This is particularly advantageous when there is a need for immediate data transmission, such as environmental monitoring and disaster response. Nodes with high CC are crucial in maintaining the network's resilience and effectiveness. They act as efficient intermediaries in situations where nodes or links fail. Their strategic positioning allows them to quickly connect with other nodes, ensuring uninterrupted communication even in unforeseen disruptions. Networks containing nodes with high CC display an increased ability to withstand faults and exhibit improved adaptability in overcoming unexpected obstacles. The CC of a node *i* is given by:

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

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

4.4. Eigenvector centrality

Eigenvector centrality (EVC)is a fundamental measure for assessing the influence of a node in a network, considering the influence of its neighboring nodes. Nodes in WSNs with high EVC exhibit robust connectivity and are closely associated with other nodes with significant influence. This dual characteristic enables them to influence the overall dynamics of the network significantly. Nodes with higher EVC are vital in transmitting information and coordinating activities within a network. They play a crucial role in facilitating fast data transmission and are essential for monitoring in real-time and responding to emergencies in WSNs applications. Moreover, nodes with high EVC contribute to the network's resilience and stability. Due to their central position and connections to other important nodes, they play a crucial role in coordinating during node or link failures. This ensures that data flow remains uninterrupted by creating alternative pathways for information to travel. The EVC of a node is given by:

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

where X_0 is the unit column matrix.

4.5. Katz centrality

Katz centrality (KC) is a comprehensive measure considering both direct and indirect pathways between nodes in a network, surpassing other centrality measures by incorporating contributions from neighbors at varying distances. This approach provides more representative centrality scores, offering a nuanced evaluation of a node's significance. In WSNs, KC is valuable for quantifying sensor nodes' importance and influence. Accounting for indirect connections clarifies a node's role in data transfer and network dynamics, which is crucial in environmental monitoring and surveillance applications. Moreover, KC's adaptability allows for modification to suit the specific requirements of WSNs, offering a flexible tool for optimizing node evaluation based on network or application needs. This adaptability makes KC instrumental in identifying and highlighting influential nodes within a network. The KC of a node *i* is given by:

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

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*.

5. RESULTS AND DISCUSSION

To identify key nodes within WSNs through centrality measures, our analysis encompasses two scenarios: networks with 30 as shown in Figure 1 and 50 as shown in Figure 2 nodes, respectively. The generation of these WSNs employs a random walk graph model that involves simulating sensor node behaviors in a specific area to evaluate network connectivity and coverage. This setup can be done in a programming environment like Python. Start by defining the deployment area, the number of nodes, their communication range, and the steps for each random walk. Then, randomly distribute the sensor nodes across the area and establish initial connections based on their proximity and communication range. Perform random walks from each node, choosing adjacent nodes within range, and optionally record these paths. Analyze the network by checking how well the area is covered and how effectively the nodes are connected, making necessary adjustments to improve network performance. Implement data collection and routing protocols based on these findings. Visualize the network layout and the paths taken by the random walks to assess the structure and performance. Finally, the simulation will be run, the results will be reviewed for adequate coverage and connectivity, and iteratively adjust and enhance the network settings as needed [40], [41].

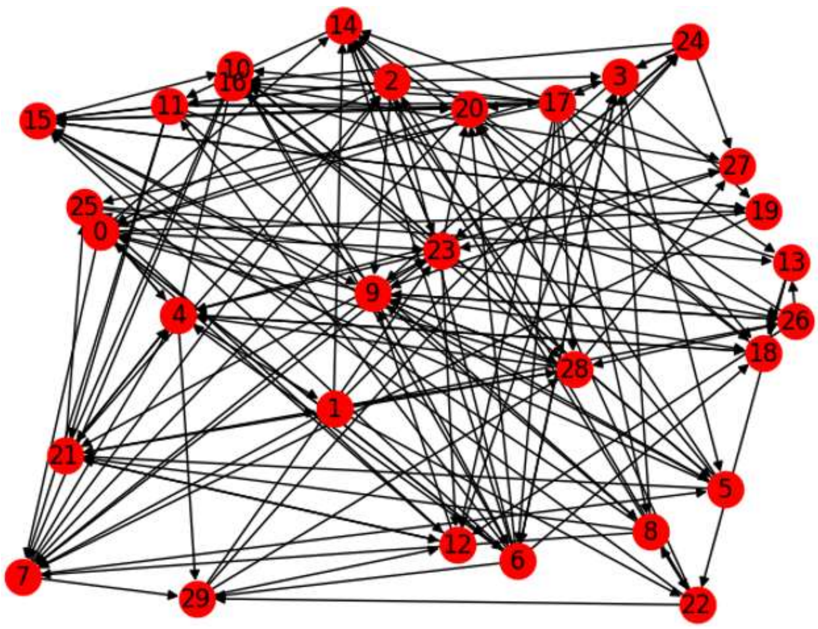


Figure 1. Graphical representation of a 30-node network generated by a random walk graph model

In the analysis of network centralities based on initial configurations shown in Figure 1 for the 30-node network and Figure 3 for the 50-node network, Figure 2 and Figure 4 display the centrality values calculated for these networks, respectively. Figure 2 sequentially illustrates the degree, betweenness, closeness, eigenvector, and Katz centrality values through subfigures 2(a) to 2(e) for the 30-node network. Similarly, Figure 4 follows with subfigures 4(a) to 4(e), each paralleling these measures for the more extensive 50-node network. Complementing these visual insights, Tables 1 and 2 list the top 10 nodes by centrality for the 30-node and 50-node networks, respectively, providing a ranked comparison of node significance based on the applied centrality metrics.

5.1. Correlation (Kendall, Pearson, Spearman) coefficient

An in-depth examination of the correlations between centrality measures enhances our understanding of a network's structural dynamics. By delineating the intricate relationships among these measures, we gain profound insights into the network's topology, fostering informed strategies in network architecture and operational management. The correlation coefficient is a pivotal numerical index, encapsulating the degree and orientation of the interplay between paired centrality metrics [25], [42]. This coefficient, ranging from -1 to 1, delineates the strength and direction of their relationship: a positive correlation indicates a concurrent increase in both variables' rankings, whereas a negative correlation reveals an inverse relationship, where one variable's enhancement corresponds to the other's decline.

The magnitude of the correlation coefficient nears ±1, and the association between the variables intensifies, signifying robust interdependency. Conversely, a correlation coefficient nearing zero suggests a weaker linkage. We used Pearson, Kendall rank, and Spearman correlation to find the correlation coefficients between measures of centrality for networks with 30 and 50 nodes in our study. The derived outcomes are methodically presented in Tables 3 and 4, clearly visualizing the relationships explored. This improvement maintains the original content's intent while enhancing clarity, precision, and readability. It emphasizes the importance of understanding network structure through centrality measures and using correlation coefficients to assess their interrelationships. The outcomes of this analysis highlight the intricate and varied nature of centrality in WSNs. The discernible differences in central nodes across the two different network sizes illuminate how structural dimensions and network scale crucially sway centrality metrics, thereby influencing the flow and dynamics of network communication. Notably, the pronounced correlations between distinct centrality metrics in the more extensive network underscore the existence of nodes with critical roles across various facets of network communication. This interconnectivity underscores the complex nature of node centrality and its critical implications for network structuring and strategic planning.

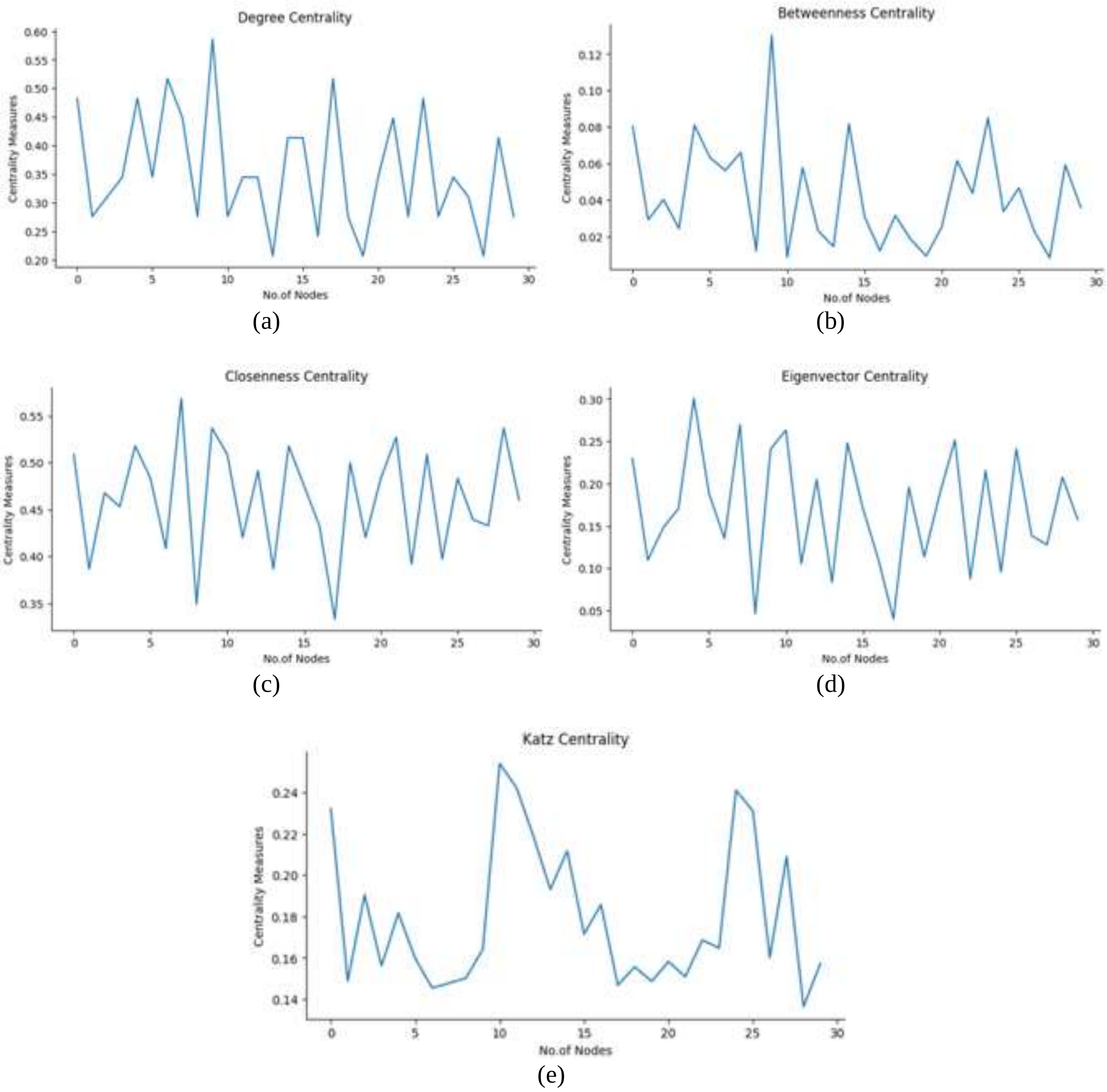


Figure 2. Graphical representation of centrality values in a 30-node network: (a) DC, (b) BC, (c) CC, (d) EVC, and (e) KC

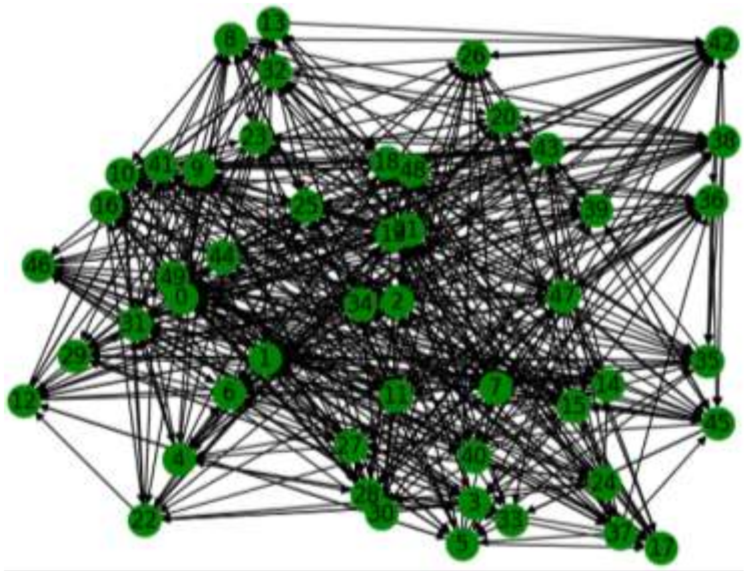
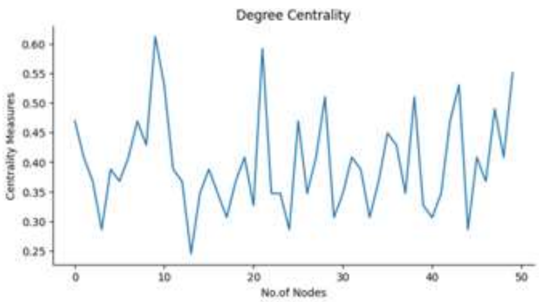
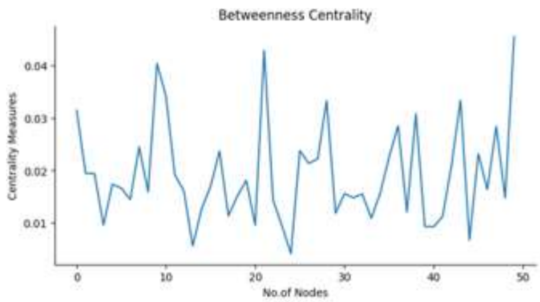


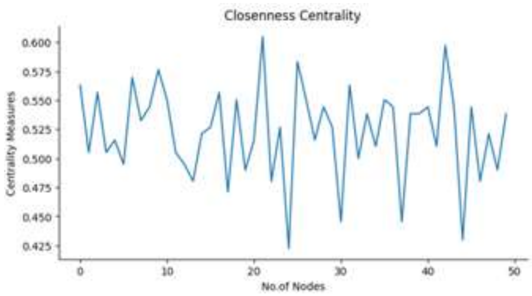
Figure 3. Graphical representation of a 30-node network generated by a random walk graph model



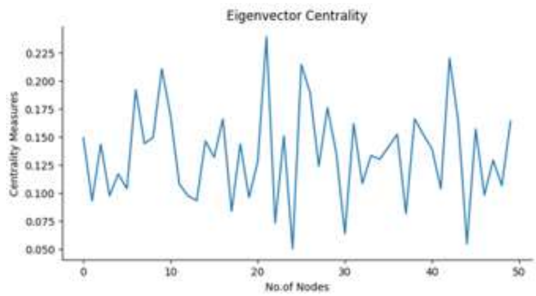
(a)



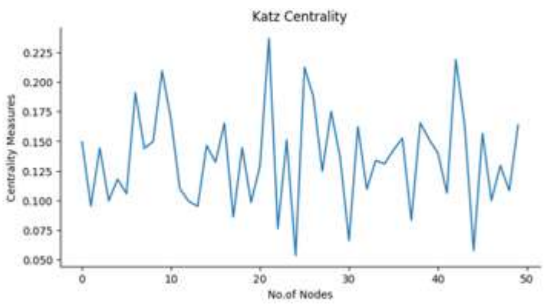
(b)



(c)



(d)



(e)

Figure 4. Graphical representation of centrality values in a 50-node network; (a) DC, (b) BC, (c) CC, (d) EVC, and (e) KC

Table 1. Node rankings: network centrality metrics in a 30-node network

Rank	DC	BC	CC	EVC	KC
1	9	9	7	4	7
2	6	23	9	7	4
3	17	14	28	10	9
4	0	4	21	21	14
5	4	0	4	14	10
6	23	7	14	25	21
7	7	5	0	9	28
8	21	21	10	0	15
9	14	28	23	23	0
10	15	11	18	28	20

Table 2. Node rankings: network centrality metrics in a 50-node network

Rank	DC	BC	CC	EVC	KC
1	9	49	21	21	21
2	21	21	42	42	42
3	49	9	25	25	25
4	10	10	9	9	9
5	43	43	6	6	6
6	28	28	0	26	26
7	38	0	31	28	28
8	47	38	2	10	10
9	0	36	16	38	38
10	7	47	10	16	16

Table 3. Correlation coefficients among centrality values of 30-node network

	DC	BC	CC	EVC	KC
			Pearson correlation		
DC	-	0.805892	0.425893	0.471324	0.507036
BC	-	-	0.551412	0.347126	0.532022
CC	-	-	-	0.941123	0.952870
EVC	-	-	-	-	0.962984
KC	-	-	-	-	-
			Kendall rank correlation		
DC	-	0.640996	0.419672	0.411895	0.441142
BC	-	-	0.386528	0.347126	0.365517
CC	-	-	-	0.838253	0.847567
EVC	-	-	-	-	0.843678
KC	-	-	-	-	-
			Spearman correlation		
DC	-	0.783487	0.514175	0.509041	0.537859
BC	-	-	0.553860	0.511902	0.514127
CC	-	-	-	0.948870	0.956668
EVC	-	-	-	-	0.955951
KC	-	-	-	-	-

Table 4. Correlation coefficients among centrality values of 50-node network

	DC	BC	CC	EVC	KC
			Pearson correlation		
DC	-	0.925835	0.597960	0.661690	0.662567
BC	-	-	0.573357	0.629785	0.629384
CC	-	-	-	0.942604	0.943999
EVC	-	-	-	-	0.999949
KC	-	-	-	-	-
			Kendall rank correlation		
DC	-	0.754454	0.409574	0.447586	0.444195
BC	-	-	0.380269	0.412245	0.410612
CC	-	-	-	0.797983	0.806304
EVC	-	-	-	-	0.991837
KC	-	-	-	-	-
			Spearman correlation		
DC	-	0.884583	0.553909	0.607291	0.605940
BC	-	-	0.542626	0.586459	0.585882
CC	-	-	-	0.921632	0.925865
EVC	-	-	-	-	0.999424
KC	-	-	-	-	-

6. CONCLUSION

The research focuses on enhancing the performance of WSNs through various centrality measures, such as DC, BC, CC, EVC, and KC. The research examines how these metrics affect routing decisions in random walk graph model of networks with 30 and 50 nodes. The main goals are to make the networks more reliable, use less energy, and have less latency by identifying key nodes. The investigation employs correlation techniques like Pearson correlation, Kendall rank correlation, and Spearman correlation to analyze the complex connections between these centrality measures. The results reveal strong and consistent relationships between centrality measures, particularly noting strong positive correlations between CC, EVC, and KC observed in both experimental scenarios. These findings contribute valuable insights into the intricate structure of WSNs, providing a comprehensive understanding of how centrality measures can be strategically utilized to boost network efficiency and reliability. The novel approach proposed in this research has the potential to advance the field of WSNs, offering concrete applications and implications for improving the efficiency of WSNs in various scenarios.

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