Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2025 (43) 3** : 1–10.
ISSN-0037-8712
doi:10.5269/bspm.79980

Evaluating Centrality-Based Key Node Identification and Performance Optimization in Barabási-Albert Wireless Sensor Networks

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ABSTRACT: This analysis focuses on examining the relevance of the centrality measures within the context of wireless sensor networks (WSNs) using the Barabási-Albert Model with 100 and 150 nodes. The centrality measures included in this work comprise Degree centrality (DC), Betweenness centrality (BC), Closeness centrality (CC), Eigenvector centrality (EVC) and Katz centrality (KC). The analysis addresses these measures to evaluate the ways they improve the performance of WSNs through key node identification. The analysis highlights the centrality measures and their role in WSNs' effectiveness, offering insights into such utilisation in routing and overall sensing reliability. Further, the complex interrelations among measures of centrality have been analysed through correlation techniques of different rigour, such as Pearson, Kendall, and Spearman. The focus on the individual metrics has provided an understanding of the centrality measures to explain further the net outcome of the performance of the network. This study addresses the interconnected developments of WSNs and offers interventional measures to enhance performance in different circumstances.

Key Words: Graph Theory, network optimization, complex networks, node importance, routing efficiency.

Contents

1. Introduction

The invention of WSNs is a pioneering creation of contemporary civilisation that enables the collection of data with the use of distributed sensor nodes. This network integrates different techniques to enable an efficient collection of data from different parts of a system to observe and measure different aspects of a phenomenon in a system. WSNs consist of a network of sensors that collaboratively monitor and assess the condition of the environment, the state of infrastructures, and several other important parameters. This is done to gather information that is useful to a wide range of disciplines. WSNs and their use in infrastructure are important and valuable [1,2]. The use of WSNs enables the achievement of new goals that are important to engineer and scientists for the deeper exploration of certain fundamentals and their applications. Understanding system behaviour in different scales, coupled with the use of WSNs to observe certain phenomena, improves system dynamics. WSNs create a wide range of theoretical and practical opportunities, and as a result extend the areas of environmental observation, health care, advanced industry, smart cities, precision farming, automated disaster mitigation, and military observation [3,4]. An example of an advantage of WSNs is their decentralised structure. This advantage permits multiple deployments of WSNs. Such deployments rigidify the set of measurements of almost any measurement

2010 *Mathematics Subject Classification:* 30C45, 30C50.
Submitted November 08, 2025. Published December 20, 2025

system, thereby weakening the influence of disturbance factors. This improved system monitoring makes significant advancements and practical uses possible in many areas [5]. An example of an advancement of WSNs is that they offer new opportunities for measurement and observation of phenomena. This puts their use toward the border of our knowledge of systems exhibiting dynamics. The use of WSNs can be a fundamental change for several branches of technology to push the performance of high-precision sensor systems even further. A significant feature of WSNs amid this modern paradigm is the term significant nodes [6,7]. These nodes are a marvel in the advancement of sensing technologies, as their use in different fields can transform entire fields. The immeasurable capabilities integrated with the communication and measurement of the surfaced phenomena are unimaginably precise. To emphasize the importance of significant nodes in enhancing the performance and functionality of a WSN, we propose their identification through distinct centrality measures.

The information in this article covers the outcome of the centrality measures of degree, betweenness, closeness, eigenvector, and Katz centrality centrality on WSNs based on the Barabási-Albert Model with 100 and 150 nodes. The central nodes of the network are of primary concern as they perform the most critical functions in optimizing the network's performance, routing the network, and enhancing the accuracy of the sensors of the entire network. This paper aims to clarify the measures of centrality that are more prominent and dominant in the relation as their centrality and performance are streamlined with the network performance toward the use of correlation methods such as Pearson, Kendall, and Spearman correlation.

2. Centrality Measures In WSNs

The focal point of centrality metrics in WSNs rests in their contribution to the optimisation of network functionality, uninterrupted data flow, and overall refined effectiveness regarding the node's sensing capabilities. Centrality metrics help to understand the analysis of the importance and the relationship of the individual nodes in the structural design of WSNs. Centrality measures enable the networks to optimally position the nodes that are critical to the sensing and transmission of data, therefore improving the efficiency of the network. Centrality measures are central to the analysis of the WSNs that determine the data transmission and processing routes [8,9]. Central to the problem are the routing protocols with the maximally optimised energy expenditure and data transfer delay that are defined as the predominant concerns of sustainable data transfer.

On the other hand, centrality measures are used to determine critical nodes that are fundamental to the strengthening of the WSNs. The appropriate placement and ensured connectivity of the described critical nodes provide the network with a heightened resilience to failures and disturbances, consequently improving the overall network reliability [10,11]. Maximising energy consumption in geo-sensor networks (GSNs) makes centrality measures a necessity. Optimising operational energy efficiency requires centrality-based strategic node placements [12]. These nodes are classified as central or peripheral. Although all nodes in a network can be interconnected, only specific nodes are capable of node configuration. These central nodes can be considered vital hubs in the network, serving as entry/exit points from the distributed sensors. They serve as the focal points of information capture and dissemination, and information transceivers and receivers, amplifying the network functionality. Centrality measures are valuable in the allocation of resources in WSNs and in the allocation of energy or bandwidth to the focal nodes. Researchers focus on the nodes with high centrality, which improves the effectiveness of the resources, resulting in improved sensing performance [12,13]. Centrality measures improve the flexible traits of the network and enhance the adaptive behaviours of the network. These centrality measures ensure that the nodes with high central impact retain central positions, and they can still be optimally placed for new operational or environmental scenarios [11, 13]. Also, centrality measures improve the optimal development of diverse routes. Optimally placed nodes with high centrality in the network improve the flow of information and the crossing links of the network, improving overall network communication. Incorporating centrality metrics in WSNs further illustrates the importance of fundamental centrality metrics to improve the utility of the networks in terms of energy, data reliability, and adaptability, among other parameters. Employing these techniques, the fundamental utility of WSNs in environmental and health-related monitoring, industrial automation, smart cities, and other equally complex fields will be significantly enhanced.

Centrality measures in graph theory, which are employed in this study to identify the most critical nodes, include [14,15]:

2.1. Degree centrality

Degree centrality allocates a value to a node in a network based on its connections as a measure of its value to the network. Each node with a higher degree centrality value possessed more connections to other nodes, thus indicating a higher 'dominance' or 'importance' within the network.

The degree centrality of a node ν_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 ith standard basis vector (the ith column of the identity matrix), and e is the vector of all entries one.

2.2. Betweenness centrality

Betweenness centrality is the set of connections formed because of its resources. The users with the highest BC scores are those riding the most significant number (or the highest average) of the shortest paths between users on the network. Such users are referred to as 'bridge' or 'focal nodes' in the network. These users are pivotal in the distribution and redistribution of the resources and information that flow across the various boundaries of the network. Moreover, their presence greatly enhances the overall network communication efficiency. The network possesses the most excellent control over its entire connectivity and redundancy.

The betweenness centrality of a node ν 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 that pass through v and σ_{ij} is the total number of shortest paths from node i to node j.

2.3. Closeness centrality

Within networks, 'closeness centrality' determines how quickly a given node can interact with other nodes. This node-to-network method involves broadcasting to every other node and averaging the distance. Imagine other nodes cluster around a node having high 'closeness centrality'. The time required to engage with every other node is reduced, and the 'closeness' node is easily accessible. These nodes are also known as periphery nodes specialized for communication. This streamlines the network and adds redundancy, as users are directed toward the focal nodes, resulting in enhanced overall performance.

The closeness centrality of a node i is given by

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

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

2.4. Eigenvector centrality

Eigenvector centrality is an analytical technique in social network analysis that characterises the importance of a node in a network with respect to other pivotal nodes to which it is connected. Unlike simpler metrics of connectivity, it assesses the breadth and depth of the connections to a node. An eigenvector central node is tied to other nodes of similarly high centrality and is thus not merely well-connected, but well-connected enough to dominate the network. This technique demonstrates the extraction of the most central nodes in the network, thereby identifying the nodes that control their structural and functional operational parameters.

The eigenvector centrality of a node i is given by

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

where X_0 is the unit column vector.

2.5. Katz centrality

In social network analysis, the importance of each node is evaluated through Katz centrality, considering both direct and indirect routes associated with attendance to and departure from each node. Relatively, there is a bias toward ascribing greater centrality to nodes that, alongside primary direct connections, are also linked to other central nodes. This process also accounts for the reach of disconnected nodes, whose centrality scores are adjusted accordingly. It allows users to pinpoint the nodes within a network that control a disproportionate amount of the data flow or even dominate the entire network.

The Katz centrality of a node i is given by

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

where I is the identity matrix of order n, α is the attenuation factor with $\alpha \in (0, \frac{1}{\lambda})$ and λ is the principal eigenvalue of A.

3. Results and Discussion

The focus of this analysis, which determines the location of the main constituents of centrality measure weighted WSNs, centres on the examination of two network configurations, using one dataset consisting of 100 nodes and another of 150 nodes. Network configurations are displayed in Figures 1 and 3, while the calculated centrality measures are shown in Figures 2 and 4. These measures are degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and Katz centrality. Each of these measures the prominence or dominion of a focal node in the network. The centrality measures for 100-node networks and 150-node networks are presented in Tables 1 and 2, respectively. These tables report the top 10 ranks for the given constructs of the networks. Such critical nodes in a network are pivotal and are likely to improve performance in data collection, processing, and transmission. For the next phase of this research, the centrality values of a network comprising 100 nodes and 150 nodes were cordialized through three different methods: Pearson's correlation, the Kendall rank correlation, and the Spearman correlation, to determine the degree of interdependence among several centrality measures.

3.1. Analysis of Correlation Coefficients

Tables 3 and 4 show the results of the correlation analysis within the 100-node and 150-node networks. The results also show the strength of correlation between the centrality metrics and the metrics of the network focus. In the 100-node network, the Pearson correlation coefficients show strong positive correlations for the majority of centrality metrics, especially for degree centrality and betweenness centrality (0.9771), closeness centrality (0.8603), eigenvector centrality (0.9335), and Katz centrality (0.94748). This means nodes that have the highest degree are also the most critical nodes in terms of the flow of information (betweenness centrality), are likely to have the shortest pathways to other nodes (closeness centrality) and have a connection to other crucial nodes (eigenvector and Katz centrality). Closer examination of the nodes using Kendall rank, Spearman and other correlation techniques sheds more light on their ordinal positioning within the network. The approximate 100-node and 150-node networks have a Pearson correlation of 0.99905 and 0.98581, respectively, demonstrating the near-perfect correlation of eigenvector centrality and Katz centrality in both networks. This is important because not only does it show agreement between the two measures, but also that one set of nodes identified as central by one measure will be equally central by the other, validating their leverage position in the network. Analysis on the 150-node network still reveals similar trends, which have Pearson showing positive, strong relations on the centrality metrics. Although the correlation is lower for the degree centrality and closeness centrality for the 150-node network (0.69889) compared to the 100-node network (0.8603), it does suggest that the larger the network has to offer, the lesser the degree of relationship there is for the connectivity and average distance the node has to the remaining nodes. The same is held for the Kendall rank and Spearman correlation, which confirmed the findings of strong positive correlation for centrality measures, especially for eigenvector and Katz centrality, which once again have almost perfect correlation. This serves to demonstrate the effectiveness of these metrics regardless of the network size.

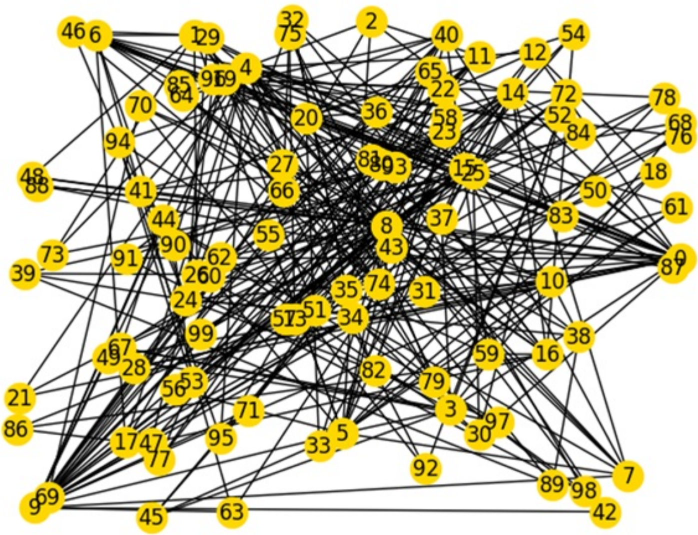

Figure 1: Network with 100 nodes: graphical illustration

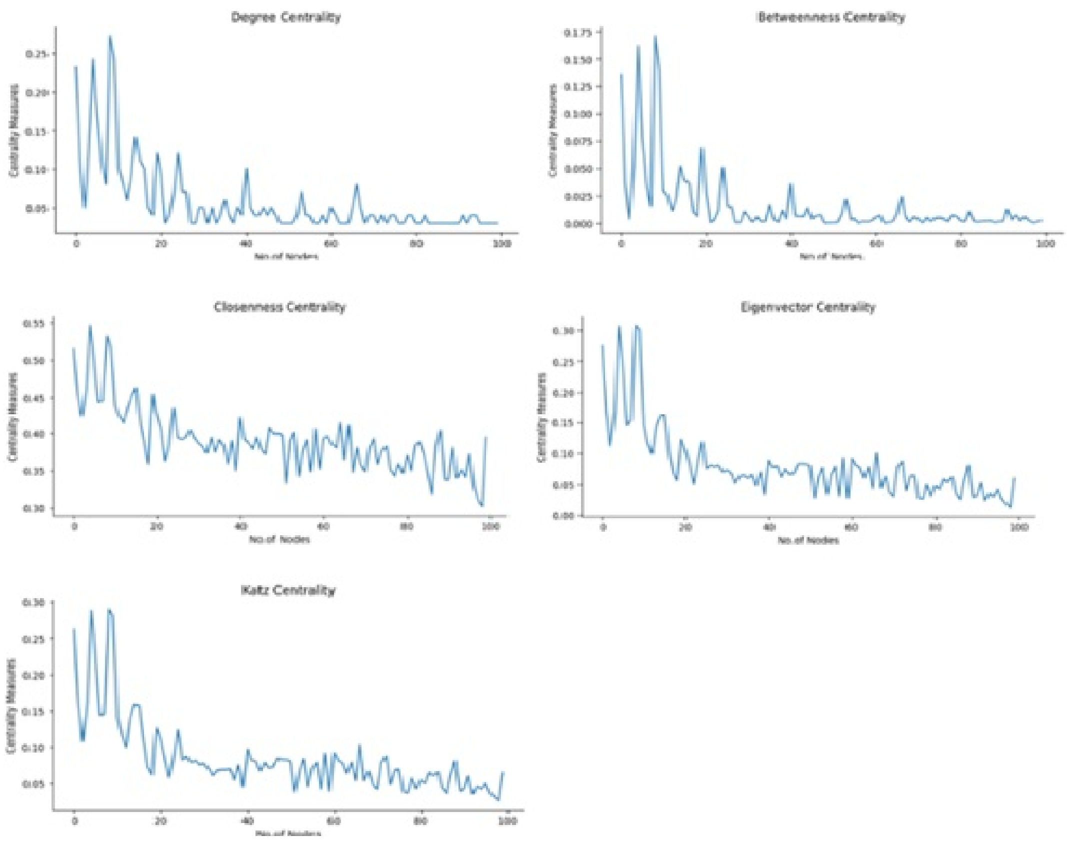

Figure 2: Network with 100 nodes: graphical illustration of centrality metrics

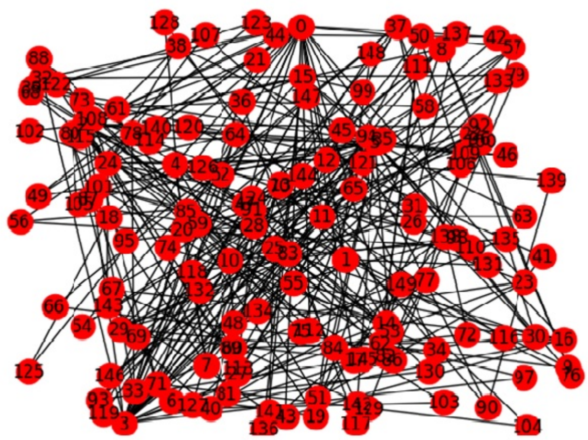

Figure 3: Network with 150 nodes: graphical illustration

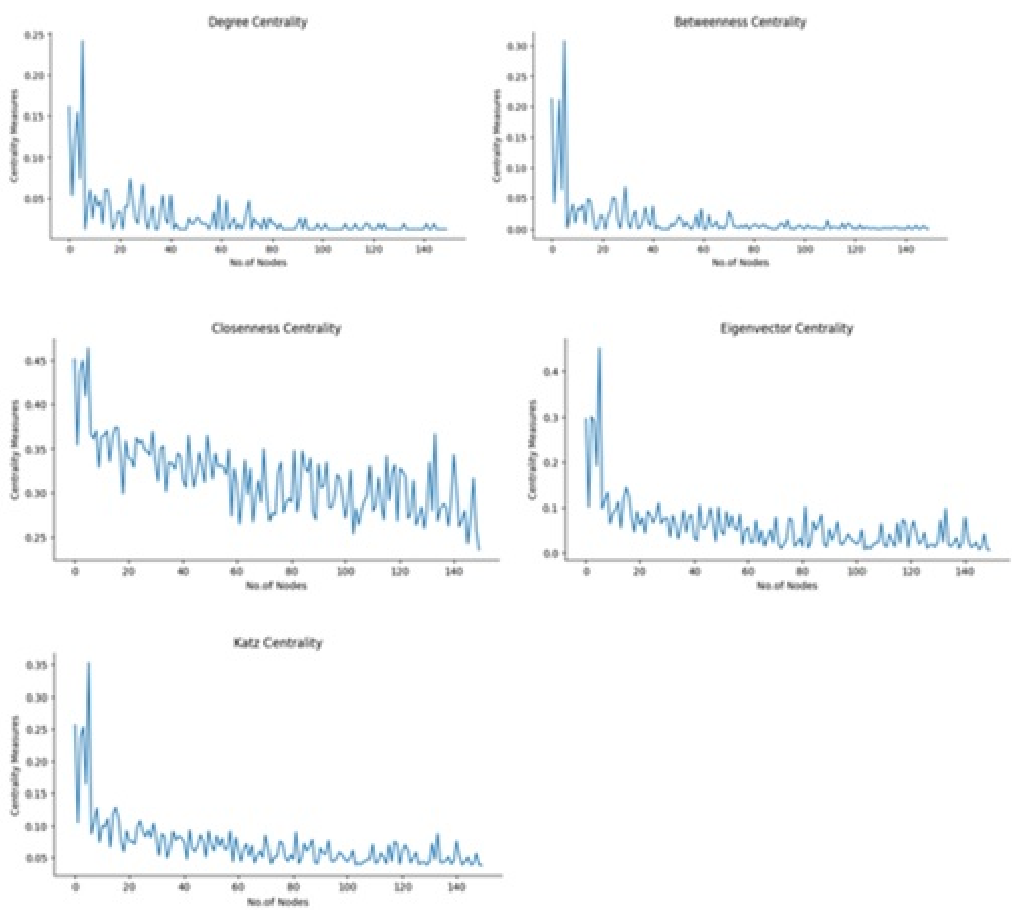

Figure 4: Network with 150 nodes: graphical illustration of centrality metrics

Table 1: Ranking of Nodes: Centrality Measures for 100 nodes

Rank	**DC**	**BC**	**CC**	**EVC**	**KC**
1	8	8	4	8	8
2	4	4	8	4	4
3	9	9	9	9	9
4	0	0	0	0	0
5	5	5	5	5	5
6	14	19	3	3	3
7	3	14	15	1	14
8	19	3	1	15	1
9	24	24	19	14	15
10	1	15	14	7	7

Table 2: Ranking of Nodes: Centrality Measures for 150 Nodes

Rank	**DC**	**BC**	**CC**	**EVC**	**KC**
1	5	5	5	5	5
2	0	0	0	2	0
3	3	3	3	0	3
4	2	2	2	3	2
5	4	29	4	4	4
6	24	4	15	15	15
7	29	24	16	8	8
8	8	25	8	16	14
9	14	14	12	14	16
10	15	15	29	7	12

Table 3: **Correlation centrality metrics for 100 nodes**

Pearson correlation

	DC	BC	CC	EVC	KC
DC	-	0.9771	0.8603	0.9335	0.94748
BC	-	-	0.82501	0.90577	0.91959
CC	-	-	-	0.95822	0.95570
EVC	-	-	-	-	0.99905
KC	-	-	-	-	-

Kendall rank correlation

	DC	BC	CC	EVC	KC
DC	-	0.81839	0.51712	0.55022	0.58801
BC	-	-	0.4173	0.3930	0.42655
CC	-	-	-	0.8416	0.84237
EVC	-	-	-	-	0.96160
KC	-	-	-	-	-

Spearman correlation

	DC	BC	CC	EVC	KC
DC	-	0.9231	0.6288	0.66653	0.70751
BC	-	-	0.5397	0.52308	0.56969
CC	-	-	-	0.9538	0.95575
EVC	-	-	-	-	0.99542
KC	-	-	-	-	-

Table 4: **Correlation centrality metrics for 150 nodes**

Pearson Correlation

	DC	BC	CC	EVC	KC
DC	-	0.98067	0.69889	0.86098	0.92932
BC	-	-	0.68510	0.86655	0.92545
CC	-	-	-	0.88964	0.87383
EVC	-	-	-	-	0.98581
KC	-	-	-	-	-

Kendall Rank Correlation

	DC	BC	CC	EVC	KC
DC	-	0.77326	0.47470	0.43424	0.57205
BC	-	-	0.46400	0.37076	0.50601
CC	-	-	-	0.82218	0.84227
EVC	-	-	-	-	0.85553
KC	-	-	-	-	-

Spearman Correlation

	DC	BC	CC	EVC	KC
DC	-	0.8839	0.5882	0.5456	0.6995
BC	-	-	0.6237	0.5217	0.67392
CC	-	-	-	0.9548	0.96401
EVC	-	-	-	-	0.96586
KC	-	-	-	-	-

4. Conclusions

The purpose of this research was to examine the importance of some centrality measures with respect to the performance of WSNs. Using networks with 100 and 150 nodes created with the Barabási-Albert model as a basis, we showed how degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and Katz centrality help find nodes needed for effective data transmission, strong network connectivity, and reliable sensing. The results show a robust relationship between other centrality measures and degree centrality. Most notably, degree centrality and betweenness centrality were almost perfectly correlated, with other centrality measures of closeness, eigenvector, and Katz centrality. High correlations between eigenvector and Katz centralities for both network sizes suggest agreement regarding the importance of nodes. That is, nodes are considered central by one measure, and nodes are considered central by another measure. This understanding adds to the knowledge on the relationships between centrality measures and their performance on a network. This research strengthens the role of centrality measures in WSNs. Also, it offers a centrality-based optimization strategy to WSNs in different domains, including the scope of the network in practice, such as the case of WSNs in environmental monitoring and industrial automation. This research can be expanded to the case of WSNs used in dynamic or heterogeneous networks, thereby increasing the performance and reliability of WSNs further.

Acknowledgments

The author thanks Vijayasekhar Jaliparthi, Department of Mathematics and Statistics, GITAM (Deemed to be University), Hyderabad, as well as the research supervisor, Alluri Sreenivas, Department of Electrical, Electronics and Communication Engineering, GITAM (Deemed to be University), Visakhapatnam, Andhra Pradesh, India. Their customized roles and immense inputs were crucial to the success of this research.

Competing interests

The author declares no competing interests.

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