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Comparative analysis of networks' centrality measures with ANOVA

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This study introduces the GDK method, combining Global Structure Model (GSM), Degree Centrality (DC), and K-shell decomposition (Ks), to assess node significance in networks. In comparison to traditional metrics (Degree Centrality, Betweenness Centrality, and Closeness Centrality), GDK is evaluated across three network types: social (Email), scientific (Netscience), and technological (Router). Analysis of Variance (ANOVA) and Kendallś correlation show that GDK consistently achieves higher correlation in ranking nodes, making it a more reliable tool. By integrating local and global centrality features, GDK identifies key nodes with both direct and structural importance, outperforming single-dimension measures. For example, in the Email network, GDK highlights both direct and bridging nodes, while in Netscience, it combines local and structural criteria to find influential nodes. The results suggest that GDK offers a more nuanced evaluation of node importance, addressing the limitations of traditional methods. Further research should explore its application to larger and more diverse networks.

Keywords: *network; centrality; ANOVA; combinations.*

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1. Introduction

Understanding complex systems across diverse domains, such as social interactions, biological pathways, and technological infrastructures, is greatly enhanced through network analysis. The analysis focuses on the concept of node centrality, which measures the significance of individual nodes in a network [1,2]. These centrality measures provide valuable insights that support decision-making, identifying key players, and gaining a deeper understanding of the structural properties of networks [3, 4].

Although numerous centrality metrics such as Degree Centrality (DC), Betweenness Centrality (BC), Closeness Centrality (CC), Eigenvector Centrality (EC), and Katz Centrality (KC) are available, the literature often lacks a thorough comparative analysis. Many studies overlook the overall performance and behavior of these metrics when applied to various network topologies. This limitation greatly hampers the ability to select the most appropriate metric for specific analytical objectives and network types [5]. As networks become more intricate, it is crucial to conduct a detailed comparative analysis to effectively apply centrality measures in different situations. This study introduces the GDK method, which stands for Global Structure Model-Degree Centrality-K-shell decomposition, as a novel approach to addressing these challenges.

In order to bridge this gap, our study utilises Analysis of Variance (ANOVA) to thoroughly compare established centrality measures with a new metric known as GDK. ANOVA is a robust statistical tool that helps us assess whether there are notable variations in average centrality scores among various groups [6]. Our goal is to use ANOVA to analyse variations in centrality scores across different network types. This will give us a strong statistical basis for making comparisons.

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Using ANOVA in this context has multiple benefits. First, it enables a structured and numerical evaluation of multiple centrality measures at the same time, facilitating the interpretation of their relative performance in a clear and straightforward manner. Additionally, ANOVA can assist in pinpointing particular network types where specific centrality measures excel or fall short. This valuable information can guide researchers and practitioners in choosing the most suitable metric for their individual requirements. Furthermore, the use of ANOVA adds a level of statistical rigour to our comparisons, ensuring that our findings are not based solely on anecdotal evidence. This enhances the reliability and generalisability of our results.

To summarise, this study seeks to address the current lack of information in the literature by offering a detailed analysis of centrality measures using ANOVA in a way that is both easy to understand and comprehensive. Through our work, we provide valuable insights into the performance of different centrality metrics across various network topologies, contributing to the field of network analysis. Our findings will help in selecting the most suitable centrality measures for various applications, thus enhancing the understanding and practical usefulness of network analysis.

2. Literature review

Centrality measures are essential in network analysis as they offer valuable insights into the significance and impact of nodes in a network. These measures assist in identifying important nodes that have a significant impact on the structure and function of the network. Understanding centrality in a network involves grasping the significance of a node and how it is measured using different centrality measures. Three commonly used centrality metrics are DC, BC and CC. Table 1 provides a concise overview of the advantages and disadvantages of each measure.

Table 1. Centrality measures strengths and limitations.

Centrality measures	Descriptions
Degree centrality [7]	**Strength:** - Measures the number of direct connections to a node. - Indicates immediate influence within the network. **Limitations:** - Does not capture indirect connections or the quality of the relationships. - Does not consider strength or quality of connections. - Limited in capturing indirect influence.
Betweenness centrality [8]	**Strength:** - Identifies nodes crucial for communication and information flow. - Highlights bridges or connectors between distinct network communities. **Limitations:** - Overemphasizes nodes in small, densely connected networks. - May not reflect importance in networks with multiple paths. - Computational complexity in large networks.
Closeness centrality [9]	**Strength:** - Measures efficiency in spreading information across the network. - Identifies nodes with quick access to others. - Useful in cohesive networks. **Limitations:** - Assumes equal relevance of all connections. - Misleading in networks with disconnected components or long paths. - Does not account for varying connection strengths.

Recognizing the limitations of individual centrality metrics, researchers have increasingly explored methods that combine multiple measures. These approaches aim to offer a more comprehensive assessment of node importance, leveraging the strengths of different centrality metrics while mitigating their individual weaknesses. One common approach is centrality fusion, which integrates various centrality measures into a unified score. This fusion can be achieved through simple averaging, weighted averaging based on domain knowledge, or more sophisticated machine learning techniques.

Example of centrality fusion:

1. **Importance of node** $C(v)$: Jiawei (2008) proposed $C(v)$, which combines DC, BC, and neighboring node degrees (DD), allowing for fine-tuning to match specific network characteristics or study objectives [10].
2. **The betweenness and katz centrality (BKC)**: Zhang et al. (2016) proposed the BKC method, which combines BC and Katz centrality (KC). The BKC method provides a fine-tuned evaluation of node importance by considering both the local influence of nodes and the influence they exert through various path lengths [11].

In addition to examining individual nodes, it is essential to grasp the broader framework of a network. The Global Structure Model (GSM) offers a thorough perspective by taking into account global metrics such as network diameter, average path length, clustering coefficient, and network density [12]. GSM assesses the contribution of individual nodes to the overall connectivity and structure of the network in a way that is both thorough and easily understandable.

Although the Global Structure Model (GSM) is thorough in its approach, it does have a few limitations. Firstly, the emphasis on global metrics may sometimes neglect important local details, resulting in a limited understanding of the significance of individual nodes in specific situations. GSM's focus on overall network properties may not fully capture the dynamic nature of evolving networks, as it tends to prioritize static structural features. In addition, GSM can be quite demanding in terms of computational resources, particularly for networks of a large scale. This can make it less suitable for real-time analysis. These limitations indicate that although GSM offers a wide perspective on network structure, it may not always provide the specific insights needed for certain applications.

The Improved Global Structure Model (IGSM) enhances network analysis to overcome its limitations. IGSM includes extra metrics and advanced techniques such as k-shell decomposition, which uncover more intricate hierarchical structures and enhance network resilience. IGSM improves our understanding of complex networks across various domains by incorporating both local and global influences [13].

The Improved Global Structure Model (IGSM) has made efforts to address some of the limitations of GSM. However, it is important to note that IGSM also has its own set of limitations. Analyzing very large networks can be challenging due to the increased computational demands caused by the added complexity and refined algorithms in IGSM. While IGSM does incorporate advanced techniques like k-shell decomposition, it may face challenges when dealing with networks that have frequent changes or unconventional structures. In addition, the hybrid approaches employed in IGSM for combining multiple centrality measures can present difficulties in fine-tuning parameters and effectively balancing various metrics. These limitations emphasize that although IGSM provides improved accuracy and detail, it necessitates additional resources and meticulous implementation for optimal results.

A metric called GDK (Global Structure Model-Degree Centrality-K-shell decomposition) was developed to address the limitations of GSM and IGSM [14]. GDK is a centrality measure that takes into account various aspects of a network to identify influential nodes in a more thorough manner. It combines the Global Structure Model (GSM), DC, and K-shell decomposition (Ks) to address the limitations of solely relying on global or local metrics. The equation for GDK formula for a node i is given in Equation (1),

$$\mathrm{GDK}(i) = \exp\left(\frac{\mathrm{Ks}(i)\times\mathrm{DC}(i)}{N}\right) \times \sum_{j\in N(i)} \frac{e^{\frac{\mathrm{Ks}(j)\times\mathrm{DC}(j)}{N}}}{d_{ij}^{\mathrm{cell}(\log_2(\mathrm{ave}_{\mathrm{iSI}}))}} \tag{1}$$

GDK takes into account the complete structure of the network, understanding how nodes are connected and the roles they play in the network as a whole. DC calculates the number of direct connections a node possesses, emphasizing nodes that have immediate influence. Ks provides a more detailed analysis by pinpointing the core structure of the network and classifying nodes according to their depth within the core. Nodes in higher k-shells are considered to be more central and influential.

Through the integration of these three components, GDK offers a thorough evaluation of a node's influence, taking into consideration its direct connections, its significance in the overall network structure, and its position within the network's central core. This approach combines the strengths of GSM and IGSM to provide a thorough and accessible analysis of node importance in different network types, overcoming their limitations. It offers a comprehensive and easy-to-understand perspective, enabling the identification of critical nodes.

3. Methodology

Figure 1 illustrates the research framework for this study. From the literature review, we identified the centrality measures to be used for comparison: DC, BC, CC, GSM, IGSM, and the proposed method GDK. This study employs a two-stage analytical approach to compare these centrality measures across various network types. The first stage involves using Analysis of Variance (ANOVA) to identify significant differences among the centrality measures. If significant differences are found, the second stage evaluates the performance of the proposed GDK method using the Kendall correlation test.

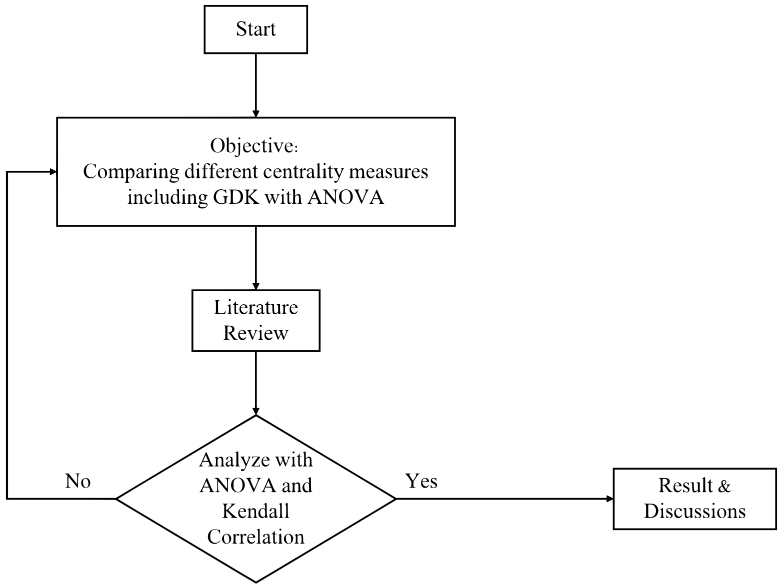

Fig. 1. Research framework.

3.1. Datasets

This study employs three distinct datasets that represent various types of networks: social, scientific collaboration, and technological. These datasets were selected to represent a wide range of real-world networks, thereby establishing a comprehensive foundation for evaluating the effectiveness of different centrality measures. Preprocessing is implemented on each dataset to ensure accuracy and consistency. Isolated nodes are eliminated, and edge weights are standardized when applicable. Table 2 summarizes the node and edge counts, density, and degree distributions of these networks. All datasets are unweighted and undirected, obtained from the Network Repository (https://networkrepository.com) [15].

Table 2. Summary of Network Datasets.

Network	Nodes	Edges	Description
Email	1005	25571	High-density social network from email communications within an organization
Netsciences	379	914	Sparse scientific collaboration network with clusters of co-authors
Router	502	1035	Hierarchical technological network representing internet router connectivity

3.2. Analysis of variances

Analysis of variances (ANOVA) is an effective method of statistical analysis that allows for the comparison of means between multiple groups, helping to identify any significant differences among them. This tool is especially valuable in our research for comparing centrality measures across various network conditions [6,16]. One of the main benefits of ANOVA is its capacity to handle multiple comparisons at once and its adaptability to different experimental designs. Using ANOVA, we can thoroughly evaluate the performance and statistical significance of different centrality measures across various network types. This method allows us to analyze the rankings and effectiveness of each centrality measure, offering a comprehensive comparison in various network contexts.

3.3. Kendall correlation coefficient

Kendall's correlation is a non-parametric statistic used to measure the ordinal association between two measured quantities. It evaluates the correspondence between the rankings of the data points and is particularly useful in situations where the data does not necessarily follow a normal distribution, or the relationship between variables is non-linear. Kendall's tau provides a coefficient value that ranges from -1 to 1, where increasing values indicate perfect agreement between two rankings [17,18].

In the context of network analysis, Kendall correlation is employed to assess the correlation between the ranks of nodes as determined by different centrality measures and an external criterion of node importance or influence. In our study, Kendall correlation is used to compare the effectiveness of traditional centrality measures DC, BC, CC, GSM, IGSM the novel GDK method. Equation for Kendall correlation is given as in Equation (2),

$$\tau = \frac{n_c - n_d}{0.5\,n(n-1)}. \tag{2}$$

4. Result and discussions

Initially, the nodes will be evaluated based on various centrality measures, and the ten most significant nodes will be determined. Tables 3, 4, and 5 display the top ten ranked nodes for each centrality measure in the Email, NetScience, and Router networks, respectively. These tables provide information on the prominence of nodes, as determined by various centrality measures and network models. Take the notation "Rank 1 for DC: 104 (71)" as an example. In this case, the number 104 is the node's identity, while 71 indicates the DC value for node 104.

Table 3. Node position for Email network.

Rank	DC	CC	BC	IGSM	GSM	GDK
1	104 (71)	332 (0.3828)	332 (0.0395)	104 (515.8471)	104 (4838.6856)	104 (979.9149)
2	332 (52)	22 (0.3817)	104 (0.0369)	332 (503.3707)	332 (4802.1983)	332 (820.7015)
3	15 (51)	104 (0.3782)	22 (0.0335)	22 (501.1832)	22 (4785.8883)	22 (809.9942)
4	41 (51)	41 (0.3776)	577 (0.0316)	41 (497.5011)	41 (4750.0736)	41 (805.4516)
5	22 (51)	40 (0.375)	75 (0.0301)	40 (490.9043)	40 (4696.4356)	40 (779.9895)
6	40 (49)	75 (0.3743)	232 (0.0277)	75 (487.1374)	75 (4685.0018)	15 (750.6963)
7	195 (47)	232 (0.3734)	134 (0.0273)	232 (486.4053)	298 (4673.0331)	232 (748.3476)
8	232 (45)	51 (0.3732)	40 (0.0265)	51 (480.6753)	232 (4670.037)	195 (739.3571)
9	20 (43)	134 (0.3699)	354 (0.0264)	134 (478.5796)	51 (4643.302)	75 (738.3966)
10	75 (43)	377 (0.3686)	41 (0.026)	377 (477.087)	134 (4615.5582)	20 (707.5227)

In the Email network (Table 3), it can observed that DC and CC generally yield similar rankings. Node 104 ranks first in both DC (71) and CC (0.3828), signifying its central position in terms of both direct connections and proximity to other nodes. Notably, BC presents a different pattern, with node 577 (Rank 4) holding a relatively low BC value (0.0316). This variation suggests that BC may not effectively capture the most influential nodes in terms of overall connectivity, unlike DC and CC, which are more consistent in identifying central nodes. Additionally, GDK consistently ranks node 104 at the top across all measures, confirming its robustness in identifying key players within the network.

Table 4. Node position for NetScience network.

Rank	DC	CC	BC	IGSM	GSM	GDK
1	43 (34)	106 (0.0664)	106 (0.0266)	106 (128.2385)	43 (140.4358)	44 (955.6695)
2	44 (27)	204 (0.0645)	184 (0.0231)	44 (121.4767)	44 (140.2482)	43 (921.7126)
3	106 (27)	184 (0.064)	328 (0.0191)	184 (118.923)	106 (137.1197)	45 (833.6304)
4	45 (21)	84 (0.0629)	204 (0.0181)	43 (117.7064)	204 (125.4203)	53 (799.3097)
5	531 (20)	326 (0.0603)	120 (0.0171)	204 (116.9759)	184 (124.0598)	54 (756.8205)
6	894 (20)	185 (0.0597)	44 (0.0168)	84 (116.6048)	84 (122.7888)	56 (748.7766)
7	893 (20)	44 (0.0595)	84 (0.0155)	185 (110.6491)	45 (118.4643)	55 (748.7766)
8	892 (20)	46 (0.0576)	326 (0.0148)	326 (106.2136)	185 (115.1861)	69 (748.7766)
9	906 (19)	215 (0.057)	46 (0.0117)	328 (105.6451)	53 (110.5472)	68 (748.7766)
10	891 (19)	220 (0.0569)	305 (0.0117)	45 (105.5319)	326 (110.1332)	204 (694.1783)

Table 5. Node position for Router network.

Rank	DC	CC	BC	IGSM	GSM	GDK
1	100 (109)	2 (0.3288)	2 (0.0668)	100 (845.1704)	100 (1620.3389)	89 (11703.718)
2	139 (96)	100 (0.3281)	0 (0.0645)	139 (829.8676)	139 (1480.9218)	384 (11265.1154)
3	350 (79)	89 (0.3271)	100 (0.0593)	2 (803.9336)	350 (1342.5666)	350 (11148.0373)
4	62 (75)	139 (0.3262)	139 (0.0534)	89 (801.4374)	89 (1260.3286)	356 (10977.0779)
5	48 (74)	0 (0.3222)	159 (0.0451)	0 (793.9552)	384 (1177.504)	369 (10730.8361)
6	242 (67)	242 (0.3176)	508 (0.0425)	242 (782.7952)	0 (1170.327)	279 (10634.9075)
7	135 (66)	384 (0.3162)	99 (0.0397)	99 (770.6143)	135 (1146.4641)	381 (10550.5609)
8	113 (66)	426 (0.315)	350 (0.0395)	62 (770.2913)	48 (1146.3471)	185 (10509.5205)
9	89 (63)	99 (0.3138)	62 (0.0389)	384 (769.8855)	2 (1140.2801)	367 (10461.6821)
10	0 (63)	216 (0.3135)	179 (0.0373)	350 (769.115)	356 (1115.4977)	100 (10457.6264)

GDK's ranking closely aligns with that of CC, suggesting its utility in identifying nodes critical for the flow of information across the network.

The NetScience network (Table 4) exhibits similar trends, with GDK consistently identifying central nodes that are also highly ranked by CC. For instance, node 43 ranks first in CC (0.0664), followed by node 44, and similarly, these nodes are ranked highly by GDK. However, BC shows greater variation, with node 328 (Rank 3) holding a relatively lower BC value, indicating that BC may be more sensitive to specific paths or clusters in the network rather than overall connectivity. This suggests that while GDK and CC capture a broader perspective of node importance, BC may be more specialized in identifying nodes that bridge distinct parts of the network. The consistent ranking of nodes by GDK highlights its effectiveness in identifying nodes that are crucial for network connectivity, making it a valuable tool for network analysis.

In the Router network (Table 5), GDK again demonstrates strong performance in identifying central nodes. Node 100 ranks first in both DC and GDK (with values of 109 and 11703.718, respectively), reflecting its high connectivity and critical role in facilitating network communication. Interestingly, BC shows a different pattern, with nodes like 139 (Rank 2) and 62 (Rank 4) receiving higher BC values, suggesting that these nodes may play more specialized roles in controlling traffic flow within the network. Despite this, GDK consistently ranks nodes such as 100, 139, and 350 highly, reinforcing its ability to capture nodes that are essential for maintaining effective communication within the network. In comparison to BC, GDK appears to provide a more comprehensive view of node importance by considering both connectivity and structural positioning within the network.

Overall, the detailed analysis of Tables 3, 4, and 5 across the Email, NetScience, and Router networks demonstrates the effectiveness of GDK in identifying central nodes. While traditional centrality measures such as DC and CC provide consistent rankings, BC exhibits more variability in its identification of key nodes. GDK, by contrast, maintains high consistency in its rankings and proves to be a powerful tool for network analysis, identifying nodes that are central not only in terms of direct connections but also in their structural roles within the network. This analysis highlights the potential of GDK to offer deeper insights into the dynamics of complex networks, making it a valuable addition to traditional centrality measures.

4.1. ANOVA analysis

The results from the ANOVA tests are presented for each centrality measure across the three network types: Email, NetScience, and Router. The ANOVA results indicated statistically significant differences between the centrality measures in their effectiveness at identifying influential nodes. Results for ANOVA analysis for each network were as in Table 6 where **SS** is the sum of square implying the measure of variation or differences in the data, **df** is the degrees of freedom, refers to the number of independent information used in the calculation and **F** is the F-test value.

In Table 6, C(Centrality) measures the sum of squares for the centrality measures, showing how much variance is explained by the differences between measures. Higher values indicate greater explained variance. F-value and P-value: The F-value assesses whether the variance between centrality measures is significant compared to within-group variance. A high F-value and a low P-value (typically < 0.05) indicate significant differences between centrality measures.

The analysis of the Email network uncovers notable variations among the centrality measures. The sum of squares for centrality measures is 3.26×10^{10}, accompanied by a remarkably high F-statistic of 23258.28 and a P-value of 0. The values suggest that the centrality measures have varying mean values, indicating their unique roles in capturing the importance of nodes in this network. This indicates that different centrality measures offer distinct perspectives and cannot be substituted for one another.

The ANOVA results for the NetScience network reveals significant findings. The centrality measures exhibit a sum of squares of 87345834, an F-statistic of 4732.56, and a p-value of 0. These findings suggest notable variations among the centrality measures, similar to the Email network. The high F-statistic confirms that the centrality measures effectively capture different aspects of node importance in the NetScience network.

Table 6. ANOVA table.

Network	Source	SS	df	F	P-value
Email	C(Centrality)	3.26×10^{10}	5	23258.28	0
	alpha	3.51×10^{-22}	1	1.25×10^{-27}	1
	Residual	1.91×10^{10}	67973		
NetScience	C(Centrality)	87345834	5	4732.56	0
	alpha	1.45×10^{-21}	1	3.95×10^{-25}	1
	Residual	3.24×10^{8}	87653		
Router	C(Centrality)	6.3×10^{10}	5	14706.01	0
	alpha	1.54×10^{-19}	1	1.8×10^{-25}	1
	Residual	1.09×10^{11}	126773		

The centrality measures in the Router network exhibit notable variations, with a sum of squares of 6.3×10^{10}, an F-statistic of 14706.01, and a P-value of 0. The results demonstrate the statistical differences between the centrality measures, underscoring their individual significance in comprehending the importance of nodes in the Router network. The high F-statistic suggests that using various centrality measures is important for capturing the complex nature of node influence.

Overall, the ANOVA highlights the importance of centrality measures in determining node importance within the network. Although changes in the alpha parameter do not impact node rankings, exploring different network parameters or additional centrality metrics may offer a more thorough understanding of network dynamics.

4.2. Kendall correlation test

The Kendall correlation test results across three distinct networks (Email, NetScience, and Router) reveal insightful patterns regarding the effectiveness of centrality measures in capturing node importance. The result for the test is in Figures 2–4.

In the Email network (see Figure 2), traditional metrics like BC consistently show lower Kendall's Tau values, indicating weaker correlations with the spreading ability metric across different alpha values. In contrast, our novel metric, GDK, consistently outperforms BC and competes closely with CC, often achieving Tau values above 0.6. This trend highlights GDK's effectiveness in identifying influential nodes in complex networks, presenting a promising alternative to traditional centrality measures.

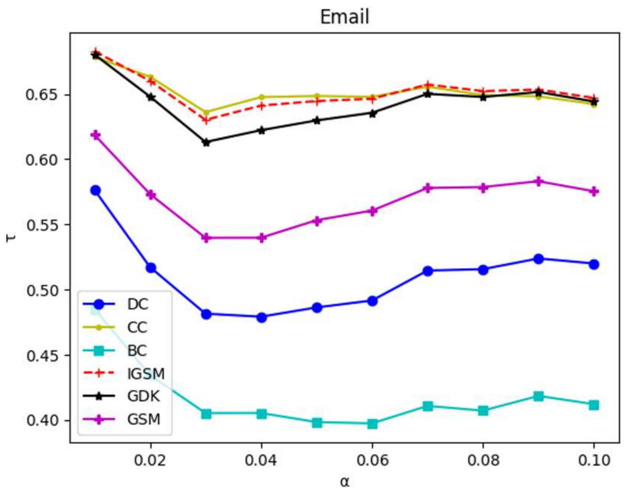

Fig. 2. Kendall correlation test for Email network.

In the NetScience network (see Figure 3), BC again exhibits the lowest Tau values, reflecting its limited effectiveness in capturing node importance relative to spreading ability. GDK shows significant improvement, with Kendall's Tau values rising to 0.68 and above across alpha values. This increase demonstrates GDK's enhanced capability to accurately assess node centrality within the NetScience network compared to other metrics.

Similarly, in the Router network (see Figure 4), GDK maintains strong performance, consistently achieving Tau values above 0.7, comparable to established measures like CC and IGSM. This consistency across different alpha values underscores GDK's reliability in identifying crucial nodes for network dynamics.

Overall, GDK emerges as a robust and promising metric for evaluating node centrality across various network types. Its ability to consistently yield higher Tau values compared to traditional centrality measures suggests that GDK offers more precise insights into node importance and network dynamics, advancing the field of network analysis.

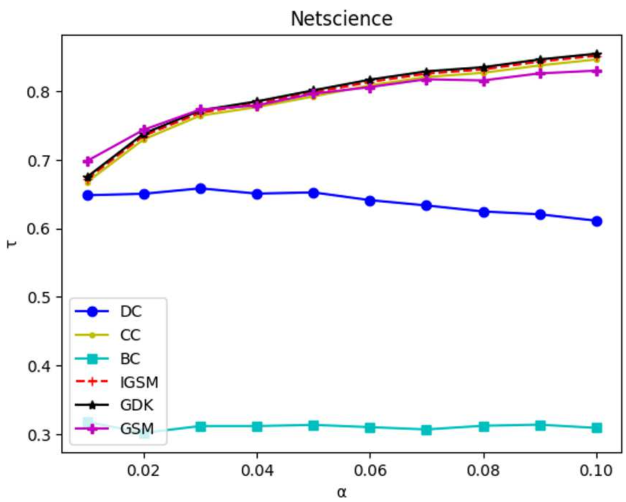

Fig. 3. Kendall correlation test for NetScience network.

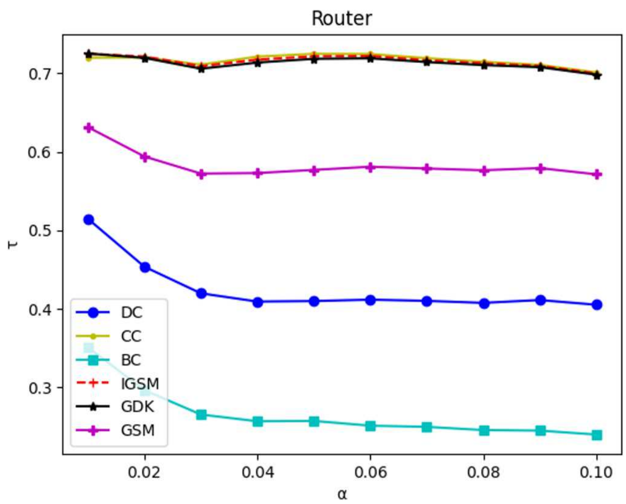

Fig. 4. Kendall correlation test for Router network.

5. Conclusions

This comparative analysis evaluated the performance of various centrality measures across different network types, with ANOVA revealing statistically significant differences among them. The results confirm the hypothesis that different centrality measures capture distinct aspects of node importance. Notably, the novel Global Structure Model-Degree Centrality-K-shell decomposition (GDK) metric consistently demonstrates strong performance across diverse networks, often aligning closely with traditional measures such as Degree Centrality (DC) and Closeness Centrality (CC). However, GDK provides additional insights into node influence, offering a more comprehensive understanding of centrality by integrating both local and global network properties.

In networks like the Email network, GDK distinguishes itself by ranking nodes not only based on their direct connections but also by highlighting their roles in bridging different segments of the network. This dual approach complements the rankings provided by DC and CC. In the NetScience network, GDK excels at identifying influential nodes by effectively capturing both local and global centrality, which is crucial for understanding the structure and influence within large-scale, complex networks. Similarly, in the Router network, GDK, along with CC and IGSM reliably identifies key nodes, demonstrating its robustness across varying network structures and its ability to handle different types of connectivity.

GDK is distinguished by its ability to combine local centrality (captured by measures like DC) with global centrality (captured by CC and other global metrics). This integration enables GDK to provide a more nuanced and holistic view of node importance, addressing the limitations of traditional centrality measures that may miss the broader network dynamics. Theoretically, this aligns with the growing recognition in network theory that centrality is not just about a node's immediate connections, but also its strategic position within the larger network context. These findings highlight the strengths and limitations of each centrality measure, with GDK offering a more balanced and insightful perspective on node influence. The introduction of GDK as a new tool advances the field of network analysis by capturing both local and global aspects of centrality in a unified framework, making it a more versatile and robust method than existing techniques.

Future research should focus on applying GDK to larger, more complex networks and exploring its potential integration with other analytical methods, such as community detection algorithms or machine learning-based models, to further enhance our understanding of complex systems and their dynamic behaviors.

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Порівняльний аналіз показників центральності мереж за допомогою ANOVA

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У цьому дослідженні представлено метод GDK, який об'єднує глобальну модель структури (GSM), ступінь центральності (DC) та K-шарову декомпозицію (Ks) для оцінки значущості вузлів у мережах. У порівнянні з традиційними метриками (ступінь центральності, проміжна центральність та близькість центральноості), метод GDK оцінюється для трьох типів мереж: соціальна (Email), наукова (NetScience) та технологічна (Router). Дисперсійний аналіз (ANOVA) та кореляційний аналіз Кендалла показують, що GDK стабільно досягає вищої кореляції у ранжуванні вузлів, що робить його більш надійним інструментом. Інтегруючи локальні та глобальні особливості центральності, GDK ідентифікує ключові вузли як із прямою, так і зі структурною важливістю, перевершуючи одновимірні показники. Наприклад, у мережі Email GDK виділяє як прямі, так і вузли-посередники, тоді як у Netscience він комбінує локальні та структурні критерії для пошуку впливових вузлів. Результати свідчать, що GDK забезпечує більш детальну оцінку важливості вузлів, усуваючи обмеження традиційних методів. Подальші дослідження мають на меті вивчити його застосування до більших та різноманітніших типів мереж.

Ключові слова: *мережа; центральність; ANOVA; комбінації.*