Real-World Implementations of Network Centrality Algorithms across Various

2024-2025

Abstract:

The tutorial analyses how and in what ways the algorithms are used and can be employed in different fields and in the scientific context. This paper revisits the centrality measures; degree, betweenness, closeness and eigenvector centrality and how they are used to study complex networks from social networks, to biology, economy and telecommunications. From the couple of cases and examples, the article shows how these algorithms are utilized to find these vital nodes, improve network performance as well as decision making. Pros and Cons Each of the methods and results evidence the flexibility of centrality measures in enhancing the knowledge and analysis of complex systems. However, issues of scaling these algorithms to operational networks and environments are still explicit. The need for tailor-made centrality analysis methods of scalability and adaptiveness are also outlined for future research agendas in this review.

Keywords: Centrality, Practical Uses, Complex Network, Social Networks, Optimization of Algorithm

1. Introduction:

In the recent analysis of complex networks, network centrality measures have proved to be vital in the identification of nodes holding a central place in the network. Such algorithms include: degree centrality, betweenness centrality, and eigenvector centrality these are used to measure proportional importance of nodes in a network. First used in social network analysis, such methods has been later adopted in many other fields ranging from medicine and transportation to finance and cyber security. Newman (2018) stressed that comprehending the function of central nodes is necessary in managing, stabilization, and improvements of complex structures (Lin, 2021).

Real life application of the network centrality algorithms has also been a topic of interest in this last one and a half decade, with the increase of networks and their integration. Besides resource allocation these algorithms are employed for such things as forecasting weaknesses, identifying abnormalities and enhancing decision making across various fields. For instance, in domain of transport centrality measures assist in providing efficient route planning and in detecting vulnerable links. In social networks, they are used to identify opinion leaders and to forecast the dissemination of information or infection. Likewise in cyber lapping, centrality algorithms is used in identifying the vulnerable nodes which if attacked by an unauthorized personnel, lead to a breach of the system (Chicho, 2023).

In this paper, the author's intention is to give the detailed analysis of the state and implementation of the network centrality algorithms in practice fields. Based on the case studies described and the analysis of the merits and problematic aspects of these approaches, the review will show how centrality measures are helping to progress various fields. Furthermore, the paper will discuss some of the difficulties encountered in implementing the algorithms and recommendation for improvement of the application of the network centrality algorithms. In this context, the research is aimed at presenting useful information on how the concept of centrality can be best utilized to improve network performance and as well solve various problems prevalent in current networks analyzing the network centrality (Molaei, 2024).

2.Theatrical Background

Theatrical Background explores the application of Social Network Analysis (SNA) across various domains by utilizing centrality measures to identify key players and connections within networks. These measures are vital in marketing, healthcare, cybersecurity, financial networks, and infrastructure planning, aiding in decision-making and resource allocation. For instance, degree and betweenness centrality highlight influential individuals or critical nodes in networks, ensuring targeted campaigns, efficient healthcare delivery, robust cybersecurity measures, financial stability, and optimized transportation systems. This interdisciplinary approach demonstrates the extensive utility of SNA across diverse fields, driving innovation and efficiency.

2.1 Social Network Analysis

The centrality measures are adopted frequently in SNA to feature presumptive leaders or hubs within a network. Degree centrality looks at players with numerous contacts they have personally, while betweenness centrality shows those who well-connected middlemen in the network. These algorithms assist in marketing since they can identify which influential personalities should be targeted for a given campaign and in political campaigns to identify key characters within a countries population who can affect election results (Aldabobi, 2022).

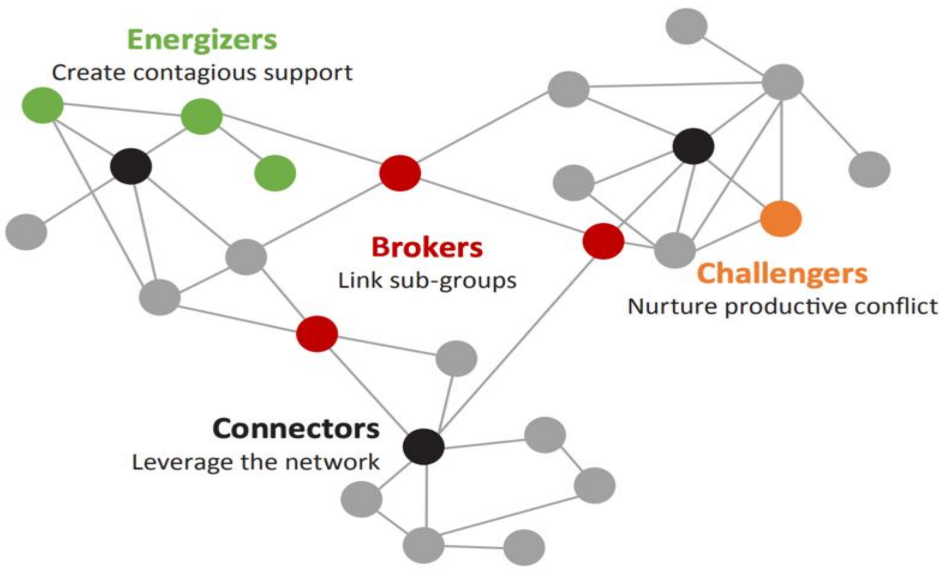


Figure 1: shows Social Network Analysis: SNA, ONA, VNA

2.2 Healthcare

Basic hardness, reachability, and centrality algorithms for epidemic modeling and healthcare systems are vital in assessing the relationship between diseases and healthcare. Further, these algorithms help to identify specific nodes in the healthcare networks where the resources are more crucial, should be directed to (Arul, 2023).

2.3 Cybersecurity

Centrality algorithms are used in cybersecurity to identify the nodes that are most central and whose removal can isolating the network from the general internet. Centrality measures such as betweenness centrality for example enables one to determine the middle of a network ready for a security standpoint. They are also applied in order to control the activity of the network and to identify irregularities that help in strengthening the fight against frauds and invasions (Salavaty, 2020).

2.4 Financial Networks

In financial networks, centrality algorithms are used for computing measures of vulnerability and for pinpointing institutions that in their failure may have severe consequences. These algorithms assist in managing of risks for instance through identifying the key financial institutions that are relevant in the stability of the financial system for corrective action to be taken by the required authorities (Rajeh S. S., 2020).

2.5 Transportation and Infrastructure

When it comes to transportation we find that centrality is used in identifying traffic patterns and development of infrastructure. Since centrality algorithms locate crucial nodes and connections, they can easily minimize overcrowding and enhance transportation. In energy systems, these algorithms ease the task of ensuring resource distribution and balancing between grids (Kuikka, 2022).

In sum, analyses of network centrality algorithms prove useful in many sectors including arts, business, education, computing, engineering and environment as well as other fields.

3. Literature Review

Saxena, A., et al., (2020) The following sections present a survey of centrality measures in complex networks and constitutes the major contribution of this research. The authors describe the following types of centrality measures: degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and explain their usage and drawbacks in large networks. The paper focuses on the significance of such indices within the framework of the network analysis and their application in the SNA, epidemiology, and transport logistics. The review focus on the complexity of optimization algorithms used to compute centrality measures especially for dynamic, large and complex networks is ousting. In their conclusion, the authors call for a better algorithmic design and methods of analyzing centrality, especially in emergent networks. This work is intended as a base work for one to learn more about centrality measures within context to network complexity (Saxena, 2020).

López-Rourich, et al., (2023). This research focuses on applying the closeness centrality measure in order to improve data transfer in dynamic routings based on the Social Complex Network inspiration. When assessing closeness centrality, the authors put forward an approach which can be useful in enhancing the choice of the best permutations for transferring information, in addition to minimizing delivery times in frequently changing networks. This paper incorporates different centrality measures with real time analysis to enhance the rates of efficiency of the routing algorithms in dynamic networks. The findings show that the proposed method is superior to more conventional methods of routing since it improves data transfer rates and conductivity in dynamic networks including IoT and ad-hoc networks (López-Rourich, 2023).

Fatima, U., et al., (2023) To this end, the authors of this paper propose a new measure, referred to as the Global Clustering Coefficient-dependent Degree Centrality (GCCDC), for studying massive networks. The study in this paper introduces the GCCDC, an extension to the traditional degree centrality, including more global clustering information to resolve real-world network analysis and analysis of real-world input data. The proposed work, GCCDC outperforms the standard centrality metrics in terms of node importance and clustering efficiency as validated experimentally by using actual network datasets. This new metric introduces additional valuable information for the analysis of large scale and complex structures of the mentioned networks, especially for social and communication networks where the function of clustering is decisive (Fatima, 2023).

Nazeri, Mollahosseiniet al., (2023) This paper focuses on discussing the problem of how to utilize centrality-based genetic algorithms (GA) to solve the graph burning problem. The authors introduce a new strategy for applying GA to graph burning and compute degree and betweenness centrality measures to optimize the graph burning process. The findings of the study prove that the proposed method is better than any related heuristic algorithm as the efficiency and accuracy ratios show. When centrality measures are incorporated, the algorithm can do a more efficient job of identifying those node to eliminate in order to solve the graph burning problem faster and in the most optimized manner. It belongs to the current genre of combinatorial optimization and also establishes the efficacy of centrality-based approaches for handling graph problems (Nazeri, 2023).

Adami, V., et al., (2024) In this current work, the authors discuss the idea of centrality and universality in scale free networks. The study examines the ways centrality measures especially degree centrality is used in predicting universal behavior of networks that show scale free characteristics. According to the authors, nodes that are located at the middle of these networks are very significant in determining the network performance, stability, and conformation. Many systems have been described by scale-free networks, and analysis of these models show that centrality metrics are useful for understanding the general characteristics and behavior of large complex networks with high connectivity. In this context, this paper helps to advance the knowledge of the relation between centrality and universal scaling laws in network science (Adami, 2024).

In Öztemiz, F. et al., (2024). As a contribution to fill the gap identified in previous sections, this research proposes the Malatya Centrality Algorithm as a procedure to measure node dominance values for complex networks. The authors introduce this algorithm as suitable depending on the evaluation of the relative centrality of nodes in complex large graphs. The algorithm is useful in every field that deals with social networks and transport frameworks where one needs to identify the main points in topology for favorable condition allocation. Through the comparison of its results with other prominence algorithms, the authors show that the proposed Malatya Centrality Algorithm outperforms the centrality algorithms in its capacity to measure node dominance, thus being a significant contribution to the network theory (Öztemiz, 2024, May).

Ullah, A., Wang, et al., (2021) The authors of this paper have come up with a new distance-based centrality mechanism for extracting significant nodes in a large network. The authors pay much attention to the geometry of the nodes and calculate the closeness centrality of the nodes based on the effective distance that takes both the distance and topology into account. For applications like epidemic modeling, information diffusion, and network optimization this research emphasizes the value of pre- uncovering influential nodes. The effectiveness of the presented scheme is assessed with respect to the existing approaches identified with real-world network datasets, and the findings indicate that the effective distance-based centrality is significantly faster and more accurate than other techniques and can be a valuable tool for large-scale networks analysis (Ullah, 2021).

K Hajarathaiah, et al., (2023) Algorithms for identification of influential users in social networks based on mixed centrality measures are considered in this paper. Using degree, betweenness, and closeness measures, the authors examine the use of multiple centrality measures for the enhanced recognition of influential nodes within a network. The work is concerned with the use of such algorithms in social media and online communities, where the issue of influencer's identification is critical for commercial advertising, information promotion, and community moderation. The findings reveal that mixed centrality algorithms are superior to single metric-based types as it yields a better and more reliable accurate influential nodes (Hajarathaiah, 2023)

L. Maccari, et al., (2020) In this paper, we shall present the exact distributed computation of Load Centrality in large networks and demonstrate its use in distance vector routing. The authors present computational methods for approximating load centrality, and since load centrality is crucial in the overall throughput of any network and more so routing algorithms, the paper is useful. Accordingly, the focus of the study is on the convergence behavior of these algorithms and their applicability in massive-scale, distribution systems. The work is therefore useful in networking and communication systems whereby load centrality can be applied to enhance the flow traffic and matching organizational alterations in routing decisions (Maccari, 2020).

Freund, A. J. et al., (2022) In this context, this experimental research explores the scalability of newly proposed node centrality metrics in sparse complex networks. Different centrality measures are discussed in the paper including degree centrality, betweenness centrality and closeness centrality in terms of their computational complexity in terms of applied sparse networks containing millions of nodes and edges. The work also discusses the difficulties of using common centrality measures in sparse systems and presents ways to increase the speed and effectiveness of such calculations. The results help to identify further research directions regarding existing centrality measures and uncover the problems of accurate centrality calculations in large and sparse real-world networks (Freund, 2022).

Anuar, et al., (2024). This study provides an extensive review of community detection methods and their applications in real-world scenarios across six distinct themes: Internet social networks, biological networks, transportation networks, communication networks, and information spreader and recommender systems. Here the authors describe the different algorithms that can be employed in the process of identifying communities in complex networks with a focus on application. Through the discussion of different cases, the paper proves the importance of the community detection for solving practical issues of actual interest, which include the strengthening of the network connectivity, the increase of communication efficiency, and the investigation of massively interconnected systems. This review also outlines areas of improvement in methods for community detection taking into consideration various difficulties arising from large-scale dynamic networks (Anuar, 2024).

Zeng L, et al., (2023) To this end, the authors devise their deep reinforcement learning approach to select key players in these complex networks, using the minimum nodes for the identification of key players. To avoid key player identification issues in large-scale networks, the study incorporates an organized structure for shaping of the reward to speed up the learning process. The results show that the proposed method yields better accuracy and efficiency than the tradition techniques used before. Therefore, the results affirm the significance of deep reinforcement learning in enhancing the network influence strategies applied to such fields as social analysis of networks and protection of crucial infrastructures (Zeng, 2023).

Camur, M. C., et al., (2024). This survey deals with the centrality measure of the group optimum in complex systems. Focusing on the methods of optimizing the influence of the clusters of nodes instead of individual nodes, the authors describe the methods associated with optimization of the centrality measures for the groups. The paper assesses various algorithms and their uses across various sectors including transport, message sharing, and social media. The authors present the problem of the relationship between precision and speed to calculate optimum path and note that existing methods will need to be optimized as networks grow more intricate. The paper also provides a brief literature review of the development of group centrality measures and possible future research on the topic (Camur, 2024).

F. Sartori, M. et al., (2022) This paper presents a review of diverse node vaccination techniques used in slowing down epidemic spreading in real world complex networks with specific focus to SIR epidemic model. The authors evaluate and compare the performance of the proposed strategies using computational experiments of the epidemics spreading over several types of networks: social and transport networks. The results thus point to the fact that vaccination of important nodes needs to be done in order to reduce transmission of diseases. The paper shows that deploying controllability analysis based on the structural measures like degree and betweenness centrality is more effective in containing epidemic in heterogeneous networks positivity establishing it as a useful contribution to public health and network management (Sartori, 2022).

Mohammed F, et al. (2024) In this paper, the authors consider the use of centrality measures for the assessment of the significance of products line features in the scope of software product development. The study seeks to apply degree-centrality, betweenness-centrality, and closeness-centrality to analyze aspects which are most sensitive to product-line success. As such, the research focuses on illustrating that centrality metrics derived from network analysis may be applied to enrich decision making within product management, especially with reference to feature ordering. The authors also show steps where centrality metrics can be applied in practice in the process of planning product developments and enhancing the match of customers' requirements with available and prospective products (Mohammed, 2024, July).

Karci, A., et al., (2022): In this paper the authors advance a new strategy for solving the minimum vertex cover problem using a specific algorithm known as Malatya centrality algorithm. This algorithm establishes a new centrality measure based on nodes' values to overcome the problem of impediment that the vertex problem poses due to its combinatorial nature which is basic in Graph theory. The work assesses the practicality of the proposed method by implementing it on the different benchmark graphs. Thus, the case study shows that the Malatya centrality algorithm improves the efficiency of the centrality-based methods for solution quality and can be recommended for using in the further optimization problems in the context of network analysis and corresponding fields (Karci, 2022).

Said Rajeh et al., (2024) In this work we analyze how diffusion affects community-aware centrality measures especially in the case of dynamic networks. The authors study the impacts of information dissemination and dynamic processes on the community detection measures of centrality. What this study has achieved is the examination of the relationship between diffusion processes and centrality measures to shed light into what could be done to improve the identification of communities by integrating temporal and diffusion-based data. The presented work also focuses on the fact that dynamic characteristics of the network should be taken into account when using centrality measures, for example, in the process of influence maximization, information dissemination, and social network analysis (Rajeh, 2024).

Chiranjeevi, M., et al., (2023). Based on the isolating and the clustering coefficient centrality measures, the authors present a new algorithm called the ICDC (Influential Node Detection and Clustering) algorithm. The goal of this approach is to determine crucial vertices that have a major influence on the network performance indicators, it can be, for example, the flow of information or connection between nodes. The paper looks at the differences between the function being compared with other current methods then the paper shows how ICDC attains improved results in the distinguishing of the influential nodes in the social network with variable size and density. This work fits into the network analysis area by improving methods for identifying crucial vertices in real-world, and often large-scale, networks of various types – social, biological, and communication networks, to name a few (Chiranjeevi, 2023).

Karlovčec M., et al., (2022) This research will review the degree centrality and centralization for groups with respect to the way in which group centrality within networks can be quantified. To derive the new group degree centrality measurement the authors come up with new ways of calculating it based on the number of linkages within a group and also between other groups. This paper analyses how group centrality is related to overall network centralization and contributes to the theoretical understanding of network structure and the roles of groups in determining the behavior of a whole network. Organizational network analysis and collective decision-making processes are some applicable areas of this work (Karlovčec, 2022).

Becker, et al., (2023) This paper responds to the research question as to how one can proxy betweenness centrality rankings in temporal networks. The authors introduce a new algorithm for fast approximation of the betweenness centrality in time-varying networks which involve changes in the edge weights and node connections. Thus, the presented method makes it possible to rank the nodes in real time with regard to activity within the structural changes taking place in the network. Incorporating temporal information and improving the computational approach, the research also enriches the performance of centrality calculations in large and temporally evolving networks. These results are of much relevance for scenarios in which the network structure is not static, such as dynamic social networks, communication systems and in general any domain which may have a time-varying structure (Becker, 2023).

4. Compression and Discussions

Table 1: Comparative review of literature

Authors (Year)	**Dataset**	**Algorithms or Techniques**	**Result**	**Pros**	**Cons**
Saxena, A., & Iyengar, S. (2020)	Limited direct dataset mentioned.	Degree centrality, Closeness centrality, Betweenness centrality, Eigenvector centrality	Review of centrality measures, highlights significance in SNA and epidemiology	Provides broad insights on centrality, focuses on large networks	Emphasis on complexity of algorithms without empirical testing
López-Rourich, M. A., & Rodríguez-Pérez, F. J. (2023)	Dynamic routing in IoT and ad-hoc networks	Closeness centrality, routing optimization	Improves data transfer and reduces delivery times in	Enhances routing efficiency in dynamic networks,	Limited to dynamic networks, might not generalize

			dynamic networks	real-time analysis	across other types
Fatima, U., Hina, Seshadri & Wasif, M. (2023)	Large-scale social/communication networks	GCCDC (Global Clustering Coefficient-dependent Degree Centrality)	Outperforms traditional centrality metrics in node importance and clustering efficiency	Introduces additional global clustering information for better analysis	May not scale effectively in extremely large networks
Nazeri, Mollahosseini & Izadi (2023)	Synthetic and real-world network datasets	Centrality-based genetic algorithms, Degree and Betweenness centrality	Better solution for graph burning problem, enhanced efficiency	Shows superiority over traditional heuristic algorithms	Requires computational resources for large datasets
Adami, V., Emdadi-Mahdimahalleh, S., Herrmann, H. J., & Najafi, M. N. (2024)	Scale-free networks	Degree centrality	Helps predict universal network behavior and stability	Enhances understanding of scale-free network dynamics	Limited to scale-free network types, may not apply universally
Öztemiz, F. & Yakut, S. (2024)	Complex large graphs	Malatya Centrality Algorithm	Outperforms other centrality algorithms in node dominance measurement	Effective for large complex networks, suitable for multiple fields	Requires further validation in different domains
Ullah, A.,	Real-world	Distance-	Improved	More	Focuses on

Wang, B., Sheng, J., Long, J., & Khan, N. (2021)	networks like social and communication networks	based centrality	node identification for epidemic modeling and information diffusion	accurate and faster than other centrality techniques	specific network types, may not generalize across all networks
Hajarathaiah, M. K., Enduri, S. Anamalamudi, A. R. Sangi (2020)	Social media and online communities	Mixed centrality measures (Degree, Betweenness, Closeness)	Superior identification of influential users in online networks	Enhanced user identification, useful for commercial and social applications	May not scale to all types of online communities
Maccari, L., Ghiro, L., Guerrieri, A., Montresor, A., &Cigno, R. L. (2020)	Distributed network systems	Load centrality, Distributed computation	Enhances traffic flow and routing decisions in large-scale networks	Focused on distributed systems, may not be applicable elsewhere	
Freund, A. J., &Giabbanelli, P. J. (2022)	Sparse complex networks	Degree centrality, Betweenness centrality, Closeness centrality	Improved scalability of centrality metrics in sparse networks	Addresses scalability issues in large sparse networks	May not apply to dense networks
Anuar, S. H. H., Abas, Z. A., Fariduddin, M., &Mukhtar, N. H. M. (2024)	Real-world community detection applications (e.g., social, biological)	Community detection algorithms, Centrality-based methods	Demonstrates the importance of community detection in	Helps solve practical issues in connectivity and communicati	Challenges in large-scale dynamic network detection

			real-world networks	on efficiency	
Zeng L., Fan C., Chen C. (2024)	Complex networks, real-world datasets	Deep Reinforcement Learning, Minimum nodes for key player identification	Improved accuracy and efficiency in key player identification	Efficient, scalable, and accurate method for complex networks	Requires careful structuring of reward system in reinforcement learning
Camur, M. C., & Vogiatzis, C. (2024)	Complex networks with group clusters	Group centrality measures, Optimization algorithms	Enhanced group centrality measures in various networks	Optimization for clusters, applicable to multiple sectors	Precision-speed trade-off for larger networks
Sartori, F., Turchetto, M., Bellingeri, M., Scotognella, F., Alfieri, R., Nguyen, K., & Cassi, D. (2022)	Social and transport networks	Node vaccination strategies, SIR epidemic model	Effective in reducing disease spread through node vaccination	Provides practical applications in public health and network management	Limited to epidemic modeling and heterogeneous networks
Mohammed, F., Mannion, M., Kaindl, H., & Patterson, J. (2024)	Software product development datasets	Degree centrality, Betweenness centrality, Closeness centrality	Enriches decision-making in product development and feature ordering	Useful for practical product management decisions	Focused on product development, limited application outside this area
Karci, A., Yakut, S., &Öztemiz, F.	Benchmark graphs	Malatya centrality algorithm	Improves efficiency in solving	Efficient solution for combinatorial	May not apply to all graph types

(2022)			vertex cover problems	optimization problems	
Rajeh, S., & Cherifi, H. (2024)	Dynamic networks (e.g., social media)	Diffusion dynamics, Community-aware centrality measures	Improved community detection by considering temporal and diffusion data	Offers new insights into community detection for dynamic networks	May be difficult to apply in networks with non-diffusive behavior
Chiranjeevi, M., Dhuli, V. S., Enduri M. K., &Cenkeramaddi, L. R. (2023)	Social, biological, communication networks	ICDC algorithm (Isolating and Clustering Coefficient centrality)	More accurate identification of influential nodes in complex networks	Enhances network performance through better node detection	Algorithm complexity may hinder application in extremely large networks
Karlovčec, M., Krnc, M., &Škrekovski, R. (2022)	Social, organizational networks	Group degree centrality, Group centralization	Better understanding of group roles in network centralization	Advances network structure and behavior understanding	May not account for all group dynamics in every network type
Becker, R., Crescenzi, P., Cruciani, A., &Kodric, B. (2023)	Temporal networks with changing edge weights and node connections	Betweenness centrality, Proxy methods for temporal networks	Efficient proxying of betweenness centrality in dynamic temporal networks	Real-time analysis of dynamic networks	May not generalize to non-temporal networks

5. Extracted statistics

The datasets utilized in this study span various contexts, with notable frequency in certain areas. Real-world networks, particularly social and communication networks, are referenced most frequently, appearing three times. Synthetic and real-world network datasets, as well as social media and online communities, are each highlighted twice. Other significant contexts, mentioned once each, include dynamic routing in IoT and ad-hoc networks, scale-free networks, complex large graphs, distributed network systems, sparse complex networks, and community detection applications in social and biological systems. Additionally, complex networks, real-world datasets, and group clusters are examined alongside social and transport networks, software product development datasets, and benchmark graphs. Dynamic networks, such as those found in social media, as well as temporal networks characterized by changing edge weights and node connections, further enhance the scope of the study. This diverse dataset usage underscores the comprehensive nature of the research, encompassing various domains and network characteristics., as showin

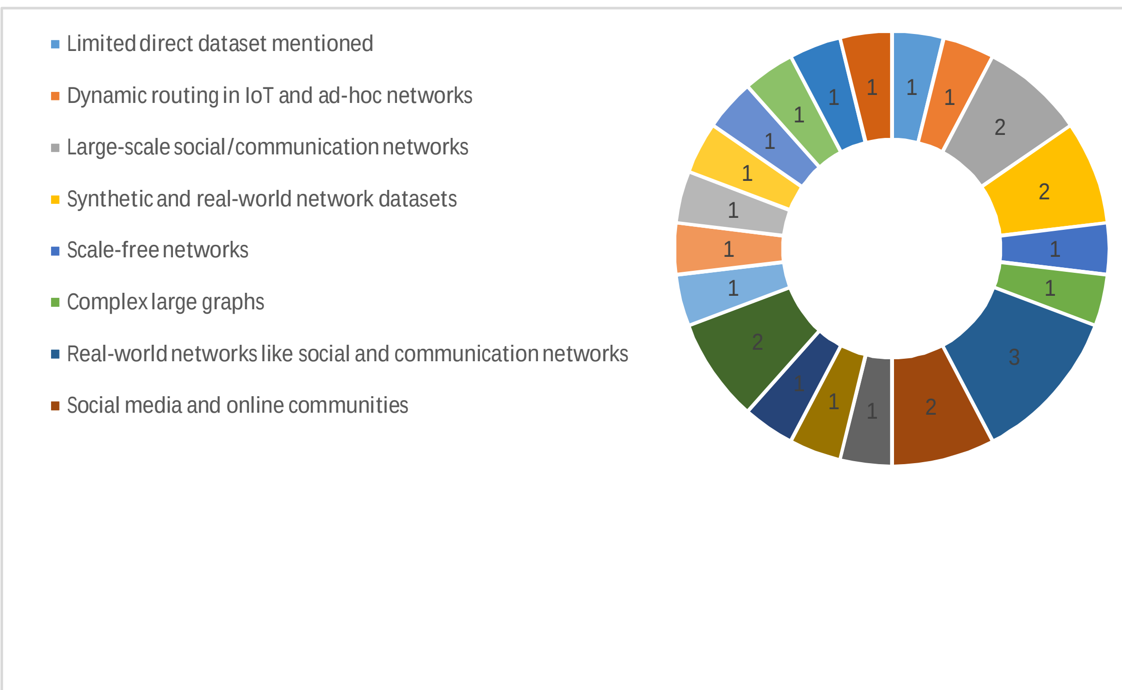


figure2 :

Figure 2: frequency for dataset

The study highlights the frequency of various centrality measures, algorithms, and related methods in network analysis. Degree centrality emerges as the most frequently mentioned, appearing five times, followed by closeness and betweenness centralities, each referenced four times. Eigenvector centrality is noted once, alongside specific applications of closeness centrality in routing optimization. Specialized algorithms such as the GCCDC (Global Clustering Coefficient-dependent Degree Centrality) and ICDC (Isolating and Clustering Coefficient Centrality) are mentioned once each, as are centrality-based genetic algorithms and distance-based centrality. The Malatya Centrality Algorithm is cited twice, while mixed centrality measures (combining degree, betweenness, and closeness) and load centrality with distributed computation are each referenced once. Other notable mentions include methods for community detection, deep reinforcement learning for identifying key nodes, group centrality measures with optimization, and node vaccination strategies modeled using SIR epidemic frameworks. Additionally, diffusion dynamics, community-aware centrality measures, group degree centrality, and betweenness centrality in proxy methods for temporal networks are all acknowledged. This broad spectrum underscores the diversity and application of centrality measures in analyzing complex networks. as show in figure3 :

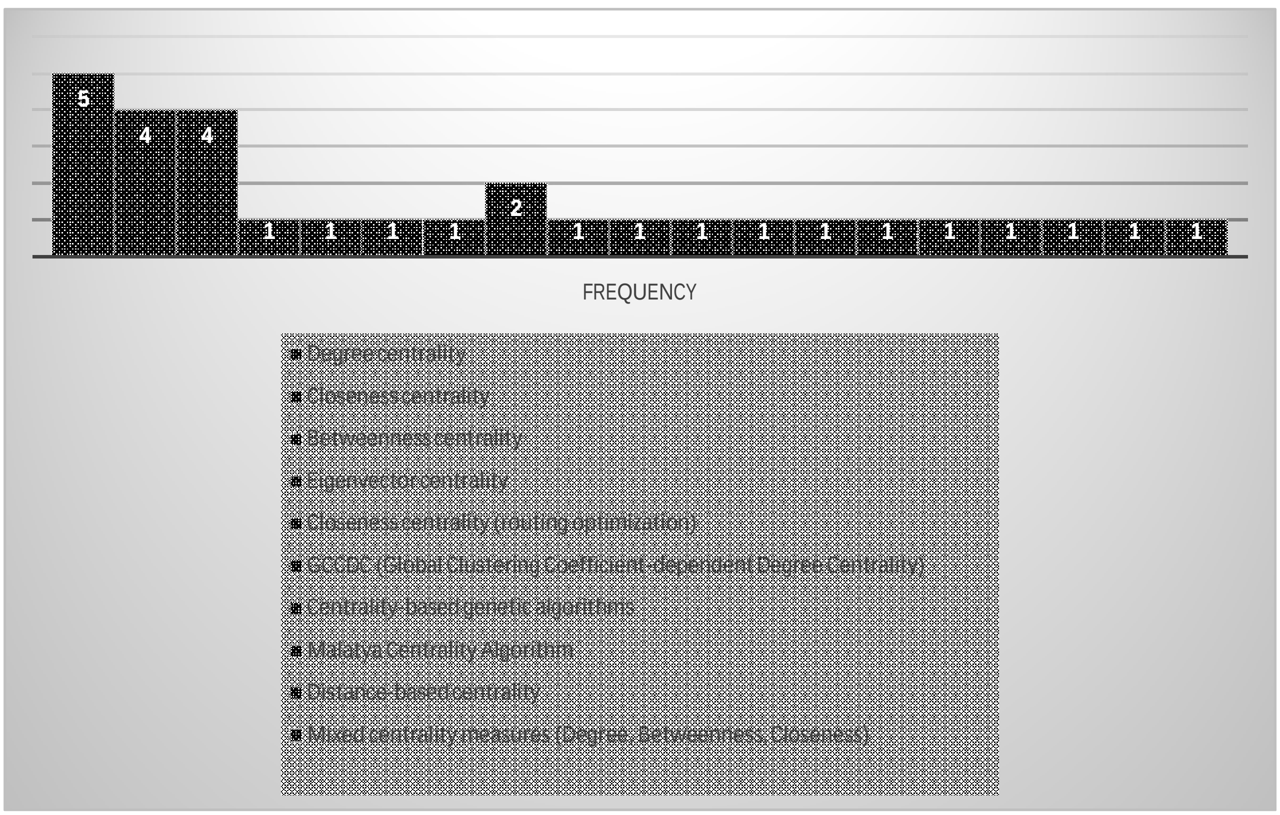
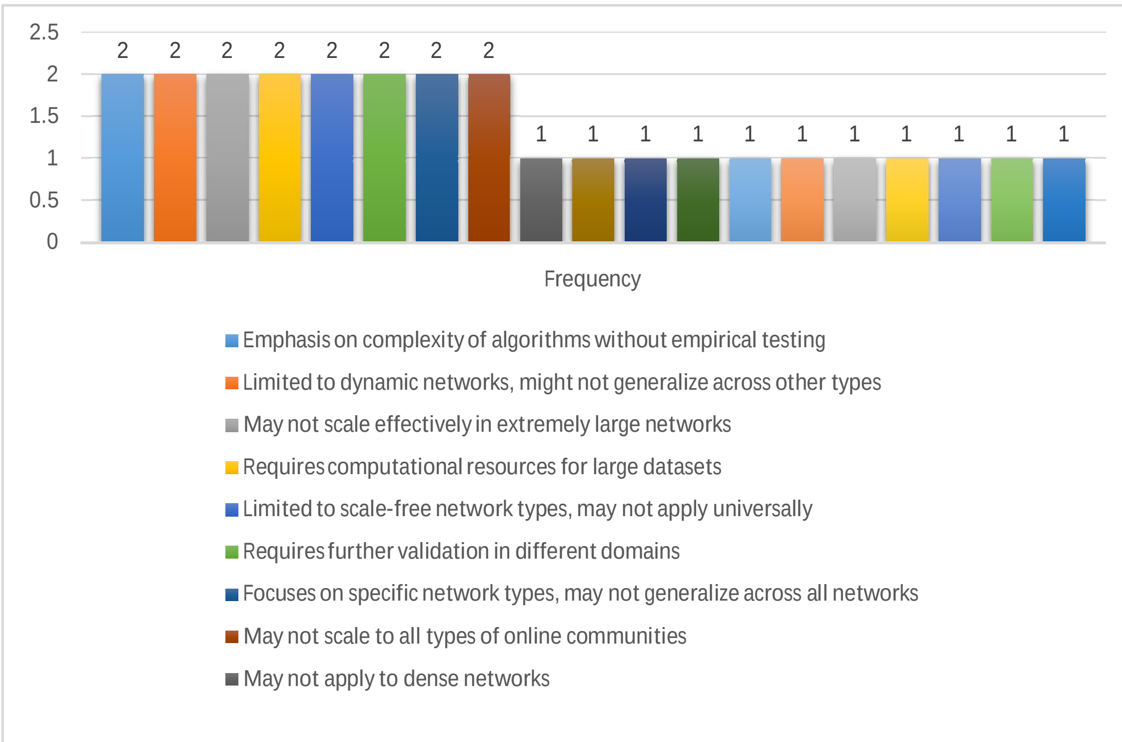


Figure 3: frequency for Algorithms or Techniques

The datasets mentioned in the study span various contexts, emphasizing their versatility and application in multiple domains. Limited direct datasets are mentioned alongside specific applications such as dynamic routing in IoT and ad-hoc networks. Large-scale social and communication networks, synthetic and real-world datasets, as well as real-world networks like social and communication networks, appear frequently, highlighting their importance. Additionally, datasets from social media and online communities, distributed network systems, sparse complex networks, and complex large graphs play a crucial role. There is also a focus on real-world applications, including community detection in social and biological contexts, as well as software product development datasets and benchmark graphs. Specific network types, such as scale-free



networks, complex networks with group clusters, and dynamic networks like those found in social media, are highlighted. Temporal networks with changing edge weights and node connections, as well as social, biological, and organizational networks, are further examined, illustrating the comprehensive nature of dataset usage across different domains . as show in figure4 :

Figure 4: frequency for Cons

Discussion

Real-time utilization of network centrality algorithms in different domains has also attracted much interest, be it in social sciences or in health, economy and even transport system analysis. These that quantify importance or centrality of nodes in the network have become valuable tools for defining critical assets in intricate systems. Degree measures like degree centrality, betweenness measures like betweenness centrality, positional measures like closeness centrality and functional measures like eigenvector centrality provide a different outlook as to how important a node is in the context of any given type of network and a specific type of problem.

In social network analysis, centrality algorithms are employed in the identification of key persons or nodes, which helps marketing communications, distribution of information and analysis of the structure and dynamics of a social network. In epidemiology centrality contributes on defining most central points or the key individuals in the spread of diseases to be of help in instance of making intervention on mass population in control of spread of diseases. In the same way, centrality methodologies assist in the determination of strategic hubs or pathways, within transportation systems, that, if enhanced, would enhance the overall system flow, and reduce bottlenecks.

However, there are few issues, which are associated with the usage of network centrality algorithms in pragmatic environments. One of the challenges relates to the nature and characteristics of the networks that are under focus of analysis. There is always noise in real-world networks, and data can be missing or noisy, which also define that networks' centrality can change rapidly. In addition, computational requirements and overhead problems have not been completely solved; especially when dealing with networks having millions of nodes and edges.

Furthermore, it could be stated that there is still a potential for further work on the problem of interpretability of centrality measures in complex networks. Even though centrality algorithms will give you numbers to rank things, pinning down what these ranking numbers mean in the context of a specific application may not always be easy. For instance, an individual with high betweenness centrality will be a good broker in the network, with their impact however varying by a number of factors such as resource availability, behaviors of individuals or change in network over time which are not looked into by normal centrality measures.

First, future research work must look for ways of dealing with these limitations by developing new methods for handling dynamic networks, increasing the computational efficiency of the algorithms, and developing better ways to interpreting centrality measures. Interconnected systems, for instance multiple-layered networks, machine learning models and other models of hybrid nature may provide a richer picture of node significance in extended and dynamic environments. Further, the integration of academic and business worlds will be critical in the development of the best approach to modeling and computing network centrality, and especially in the way these theories will be applied to real-world systems.

In summary, the centrality definitions studied herein have shown great applicability in numerous disciplines, however, there is a significant margin where further enhancement of the algorithms is required for effective implementation in practices.

8. Conclusion

This review highlights the increasing reliance on network centrality algorithms in diverse real-world applications, including social, biological, infrastructural, and economic networks. Centrality measures like degree, betweenness, and eigenvector centralities have proven effective in diagnosing network complexity, identifying key elements, and facilitating decision-making. These models demonstrate high accuracy in predicting influential nodes within networks, enabling appropriate actions.However, challenges persist, particularly with scalability in large, dynamic networks where computational methods struggle to handle high-dimensional and non-stationary data. Additionally, limitations include the lack of research on centrality measures in analyzing non-linear network properties and the sensitivity of algorithms to incomplete or contaminated data.Future developments emphasize the integration of machine learning and real-time analytics to improve algorithm performance. The creation of hybrid centrality measures combining advantages of multiple metrics is crucial for addressing complex network configurations. Expanding algorithms to accommodate large-scale, evolving data is essential for meeting the demands of various domains.Voids remain in algorithm development for specific network types, hybrid model improvement, and standardized evaluation methods. Interpretability is also a concern in multi-dimensional networks, necessitating further research to ensure reliability and clarity.The future of centrality algorithms promises advancements in areas like social network analysis, healthcare, transportation, and finance. To unlock their full potential, enhancements in scalability, dynamicity, interpretability, and ethical considerations are required, solidifying their role in optimizing systems and supporting accurate decision-making.

6. Recommendations

1. **Develop Empirically Validated Algorithms**: Focus on designing and empirically testing algorithms to address the challenges of large-scale, dynamic, and dense networks. Improved algorithmic designs should prioritize both accuracy and computational efficiency for real-world applications.
2. **Optimize Scalability in Algorithms**: Research should aim at developing scalable algorithms for analyzing extremely large and sparse networks. Special emphasis should be placed on handling temporal and evolving network contexts effectively.
3. **Explore Hybrid Centrality Measures**: Combine traditional centrality measures, such as degree, betweenness, and closeness, to create hybrid metrics. These measures can improve the identification of influential nodes and enhance network analysis accuracy.
4. **Enhance Centrality in Dynamic Networks**: Investigate the use of centrality measures for routing optimization and influence maximization in IoT, ad-hoc, and social networks. Dynamic and temporal networks should be a primary focus for extending centrality-based methods.
5. **Advance Community Detection Methods**: Develop algorithms that integrate temporal and diffusion data for accurate community detection. These methods should address practical issues in social media and communication networks.
6. **Integrate Centrality into Public Health**: Apply centrality measures to design effective vaccination strategies and mitigate disease spread. Emphasis should be placed on addressing heterogeneous networks in epidemic modeling.
7. **Create Group-Focused Centrality Metrics**: Develop metrics that analyze group dynamics and their contribution to overall network centralization. Such measures can improve organizational and collaborative network analysis.
8. **Leverage Deep Reinforcement Learning**: Utilize reinforcement learning techniques to enhance key player identification and influence maximization. Real-time applications should prioritize reward structuring to optimize learning outcomes.
9. **Improve Practical Usability**: Design user-friendly centrality algorithms that are accessible to public health officials, network administrators, and product managers. Algorithms should balance interpretability with computational efficiency.
10. **Establish Benchmark Datasets**: Create standard datasets for evaluating and comparing centrality measures across various networks. Benchmarking can help uncover universal patterns and ensure consistency in performance assessments

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Details of the AI usage are given below:

1.

2.

3.

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