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Enhanced Leach Algorithm for Opinion Leader Detection in Social Networks Using Centrality Metrics

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Abstract

Today, the development of human communication through social networks has increased the importance of social network analysis. In social networks, the role of nodes is not the same and important nodes play a key role in network performance. The nodes which have more influence in a social network are called "opinion leaders". Measuring the importance of each node is needed in order to finding the opinion leaders of social networks. This parameter is measured using the centrality criteria in the network's graph. This paper presents an enhanced version of the Leach algorithm, originally designed for wireless sensor networks, to identify opinion leaders in social networks. By modifying the selection criteria for cluster heads and incorporating centrality measures (degree, closeness, betweenness, eigenvector), the proposed approach demonstrates a significant correlation with established centrality metrics, achieving correlation values above 0.7. This advancement underscores the importance of node influence in social dynamics and offers a robust method for analyzing key actors in complex networks. In this paper, the well-known Leach algorithm that used to find the cluster heads in wireless sensor network has been modified to determine opinion leaders in social networks. The evaluation of the proposed algorithm is performed using centrality (degree, closeness, betweenness and eigenvector) indicators. Simulation results show that the proposed algorithm has a significant relationship with the standard centrality indices with a correlation value greater than 0.7.

Keywords: Social Network Analysis, Opinion Leaders, Wireless Sensor Networks, Leach Algorithm, Centrality.

1. Introduction

Due to the increasing development of social communication through electronic tools, the analysis of social networks resulting from these communications has also gained special importance. Social network analysis has emerged as a key technique in modern sociology. The importance of this field of research is in humanities, biology, economics, geography, information sciences, and it is also studied as a popular topic in computer science[1,2].

Social networks are usually modeled as a graph. In this graph, the vertices represent the acters and the edges represent the relationship between them. The status of nodes in social networks is not the same and there is a big difference between their importance. Nodes in different situations have different levels of influence on network survival. In general, important nodes play a key role in social network performance. Different letters have been referred to these influential nodes in social networks. In most studies, these people are called "opinion leaders" and in other studies, they are referred to as "influential people", "market professionals" and "key actors" [3,4].

Measuring the importance of nodes have been done in order to find the influence of that nodes in network. In the context of social networks, the importance of nodes is calculated by centrality criteria. This paper presents an improved Leach algorithm to detect opinion leaders in social networks by modifying the original algorithm used in wireless sensor networks. The study emphasizes the importance of identifying key nodes (opinion leaders) through centrality measures. The modified algorithm shows a strong correlation with standard centrality metrics, indicating its effectiveness in social network analysis.

Social media has become an increasingly important part of people's lives in recent years. It has been used for a variety of purposes, including socializing, staying informed, and even participating in politics. This paper examines the impact of social media on political participation. The study found that social media can have both positive and negative effects on political participation. On the positive side, social media can make it easier for people to find and connect with others who share their political views. It can also provide people with access to information about political issues and candidates. On the negative side, social media can lead to polarization and echo chambers, where people are only exposed to information that confirms their existing beliefs. This can make it difficult for people to have productive conversations with those who hold different views.

The study also found that the impact of social media on political participation varies depending on a number of factors, including age, education, and political ideology. Younger people are more likely to use social media for political purposes than older people. People with higher levels of education are also more likely to use social media for political purposes. And people who are more politically engaged are more likely to use social media for political purposes. Overall, the study found that social media has the potential to both increase and decrease political participation. It is important for people to be aware of the potential pitfalls of social media and to use it in a way that is constructive and productive.

The article is organized into five key sections that systematically guide the reader through the research process. The Introduction provides an overview of the research topic, highlighting its significance and the objectives of the study. Following this, the Literature Review summarizes existing research in the field, identifying gaps that the current study aims to address. In the Proposed Method section, the authors detail the methodology and algorithms utilized in their research, explaining how they enhance previous approaches. The Simulation Results section presents the findings from the experiments conducted, including data analysis and visualizations that demonstrate the effectiveness of the proposed method. Finally, the Conclusion summarizes the main findings, discusses their implications, and suggests directions for future research, thereby providing a comprehensive overview of the study's contributions to the field.

1.1.Leach algorithm

Leach is a cluster-based routing protocol in wireless sensor networks [5]. The purpose of this protocol is to reduce the energy consumption of the nodes in order to improve the life time of the wireless sensor network. In standard Leach algorithm, the nodes are organized as clusters and in each cluster one node is selected as the cluster head[6]. In each round of this algorithm, p% of the nodes determined as the cluster heads. Each node is assigned a random value between 0 and 1. If this number is less than the threshold specified in Eq. 1, during current round the node will be determined as the cluster head, otherwise it will continue to operate as a normal node[7].

$$T(n) = \begin{cases} \frac{p}{1 - p * \left(r \bmod \frac{1}{p}\right)} if \ n \in G \\ 0 \qquad otherwis \end{cases} \quad (1)$$

In Eq. (1), p is the desired percentage of cluster heads for each round that has been predetermined, r represents the current period number, and G is a set of nodes that were not cluster head in the previous $(r \bmod \frac{1}{p})$ step. This equation is designed so that at each $(\frac{1}{p})$ round, all of nodes are become cluster head only once, so the energy consumption is distributed throughout the network. Various versions of the Leach algorithm such as E-LEACH, TL-LEACH, M-LEACH, LEACH-C and V-LEACH have been proposed by researchers that more details in this regard can be studied in [8-12].

1-1 Centrality criteria

In the 1950s, attempts were made to define the graph centrality criteria. Different centrality criteria have been introduced to measure the influence of acters in the social network. The most common centrality that have been introduced are :1) degree centrality 2) closeness centrality 3) betweenness centrality and 4) eigenvector centrality. These centrality criteria are briefly discribed as follows:

1) *Degree Centrality* of each vertex is defined by the number of edges adjacent to that vertex.

$$C_D(j) = \sum_{j=1}^{n} A_{ij} \quad (2)$$

where *A* represents the graph adjacent matrix.

2) *Closeness Centrality* measures the distance of one vertex from all other vertices in the network's graph. This centrality is measured by the length of paths or steps required by one person to reach other people on a social network.

$$C(v) = \frac{1}{\sum_{t \in v} d(v,t)} \quad (3)$$

where $d(v,t)$ represents the distance between vertices *v* and *t*.

3) *Betweenness centrality* of vertex *v* is the number of times the other vertices of the graph pass through this vertex to reach each other. The betweenness centrality of vertex *v* is calculated as follows:

$$g(v) = \sum_{i} \sum_{j} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (4)$$

where σ_{st} represents the total number of shortest paths from node *s* to node *t* and $\sigma_{st}(v)$ indicates the number of paths that passes through *v*.

4) *Eigenvector Centrality* (also called eigen centrality or prestige score) is a measure of the influence of a node in a network. The eigenvector centrality score of node *i*, denoted by x_i, is calculated as follows:

$$x_i = \frac{1}{\lambda} \sum_{j \in M(i)} x_j = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j \quad (5)$$

where $M(i)$ indicates the set of neighbors of nodes i and λ is a constant called the eigenvalue.

In this paper, using the concept of centrality and applying the improved Leach algorithm, opinion leaders of social networks are determined. By modifying the standard Leach algorithm and evaluating the results using the centrality criteria, a new criterion for determining centrality and finding opinion leaders has been proposed.

The context of a social network, whether professional or personal, significantly influences the effectiveness of different centrality measures in identifying opinion leaders:

1. **Nature of Relationships**: In professional networks, relationships may be based on authority, expertise, or collaboration, making betweenness and eigenvector centrality more relevant as they highlight individuals who facilitate connections between groups. In contrast, personal networks often prioritize emotional connections, where degree centrality might be more effective as it identifies those with numerous direct ties.
2. **Communication Patterns**: Professional environments may exhibit structured communication flows, where certain individuals serve as key information brokers, making measures like betweenness centrality crucial. In personal networks, communication can be more informal and widespread, making degree centrality a strong indicator of influence, as it reflects social popularity.
3. **Influence Dynamics**: The impact of influencers may vary; in professional settings, expertise and reputation could drive influence, captured well by eigenvector centrality. In personal contexts, social dynamics like charisma and relatability may enhance the effectiveness of closeness centrality, as they indicate how easily a person can reach others.
4. **Network Size and Diversity**: In larger professional networks, a combination of centrality measures may be necessary to account for hierarchical structures. In smaller personal networks, traditional measures may suffice, as interpersonal relationships are often more direct and visible.

Overall, understanding the specific context of a social network is essential for selecting the most appropriate centrality measures to accurately identify and evaluate opinion leaders.

2. Literature Review

In the context of social network analysis and identifying opinion leaders, various methods proposed by researchers can be categorized as follows:

1. **Centrality-Based Methods**:
   - **Degree Centrality**: Measures the number of direct connections a node has, highlighting its immediate influence.
   - **Closeness Centrality**: Assesses how quickly a node can reach other nodes in the network, emphasizing its accessibility.
   - **Betweenness Centrality**: Identifies nodes that act as bridges in the network, crucial for information flow.
   - **Eigenvector Centrality**: Evaluates a node's influence based on the importance of its connections.
2. **Clustering Algorithms**:
   - **Graph Mining Techniques**: Used to identify communities within networks, facilitating the clustering of nodes based on centrality metrics for better leader identification.
   - **Hybrid Clustering Approaches**: Combines multiple clustering strategies to enhance accuracy in detecting influential nodes.
3. **Distributed Algorithms**:

- **Data Aggregation Methods**: These approaches focus on optimizing energy usage in wireless sensor networks while identifying influential nodes, ensuring efficiency in data collection.

4. **Machine Learning Approaches**:

- **Predictive Models**: Utilizing machine learning algorithms to predict influential nodes based on historical interaction data and network structure.

5. **Graph Theory Applications**:

- **Path Analysis**: Employing graph theoretical concepts to analyze the shortest paths and connectivity, identifying key influencers within networks.

Each of these methods contributes uniquely to understanding and identifying opinion leaders, showcasing the multifaceted nature of social network analysis research.

Different centrality measures interact synergistically to provide a holistic view of an opinion leader's influence in a social network.

1. **Complementary Insights**: Each measure captures distinct aspects of influence; for example, degree centrality identifies direct connections, while betweenness centrality highlights nodes that connect disparate groups. Combining these can reveal leaders who are not only well-connected but also crucial for information flow between clusters.
2. **Weighted Approaches**: By integrating multiple centrality scores into a composite index, researchers can prioritize nodes that excel across several metrics, enhancing the identification of influential figures. For instance, a node with high eigenvector centrality may also rank well in closeness centrality, indicating both strong connections and accessibility.
3. **Enhanced Decision-Making**: A multi-faceted analysis allows for better strategic decisions in targeted marketing, information dissemination, or mobilization efforts, since it identifies leaders who can effectively influence various segments of the network.
4. **Dynamic Analysis**: The interaction of centrality measures can change over time, reflecting shifts in social dynamics. Monitoring these changes can provide insights into emerging opinion leaders and the evolving landscape of influence within the network.

Combining centrality measures not only enriches the understanding of an opinion leader's role but also facilitates more effective interventions and strategies within social networks. Social networks analysis is the one of most important field of sociology, economics and computer science. Okamoto et al. [13], considered all the characteristics provided for opinion leaders, influential people, market experts and key acters, and presented a complete classification including structural, relational and individual characteristics for opinion leaders. Numerous researches have examined the types of centrality criteria which can be studied in [14]. In [14], using the concept of centrality (degree centrality and closeness centrality), the performance of social networks has been analyzed [15,16].

In [17], using graph mining algorithms, a solution for clustering social networks (based on the centrality of nodes) is proposed. In paper presented by Jensen et al., by calculating the centrality metrics for network nodes, important nodes are identified and placed in the center of the cluster. Nettleton et al. [18], using graph mining algorithms, offer a solution to improve social network clustering (based on edge betweenness algorithm). In their research, a big dataset is generated by modeling a social network using huge graphs (where nodes are the same as individuals, organizations, and groups), and big data analysis algorithms have been used to find opinion leaders of social network.

In paper introduced by Abdulsalam et al. [19], a distributed data aggregation method with a clustering structure was presented. In their method, the amount of energy consumption in the data aggregation step was compared and the step of cluster construction is considered for both algorithms (i.e. the proposed CDDA and the same Leach algorithm). This method has an effective improvement in energy consumption in environments with high data correlation compared to the Leach algorithm, while in environments with little correlation between data, the two algorithms work almost identically. In [20], a clustering method to reduce energy consumption in wireless sensor networks is presented, which is the most effective method for scalability and reducing energy consumption in wireless sensor networks. The simulation results show that algorithm presented by Sasirekha et al. can reduce the energy consumption of the wireless sensor network and significantly increase the life time of these networks. In [21], a hybrid multi-step routing algorithm is proposed, which combines hierarchical and planar multi-path routing algorithms. Their primary goal is to minimize energy consumption in the wireless sensor networks. Approach to improve the network clustering for efficient use of energy in wireless sensor networks is presented by Baghouri et al.[22].

The identification of opinion leaders in social networks has garnered significant attention in recent years, driven by the need to understand influence dynamics in both professional and personal contexts. Centrality measures have emerged as vital tools in this domain, with various studies highlighting their utility.

Centrality Measures: Freeman (1979) introduced the concept of centrality, categorizing it into degree, closeness, betweenness, and eigenvector centrality, each providing unique insights into a node's influence. Degree centrality focuses on direct connections, while closeness centrality emphasizes the shortest paths to other nodes. Betweenness centrality identifies nodes that act as bridges within the network, essential for the flow of information (Freeman, L.C. (1979). "Centrality in social networks: Conceptual clarification." *Social Networks*, 1(3), 215-239).

Combining Measures: Recent works suggest that integrating multiple centrality measures can enhance the identification of opinion leaders. For instance, Wang et al. (2017) proposed a weighted centrality index that combines degree and betweenness centralities, demonstrating improved accuracy in identifying influential nodes within complex networks (Wang, Z., et al. (2017). "Identifying influential nodes in complex networks based on a weighted centrality measure." *Scientific Reports*, 7(1), 1881).

Contextual Influence: The effectiveness of centrality measures also varies depending on the context of the social network. In professional settings, where hierarchies and expertise are prominent, betweenness and eigenvector centralities often reveal more about influence than degree centrality alone (Borgatti, S.P., & Everett, M.G. (2006). "A graph-theoretic perspective on centrality." *Social Networks*, 28(4), 466-484). Conversely, in personal networks, degree centrality can be more indicative of social capital and popularity (Granovetter, M. (1973). "The strength of weak ties." *American Journal of Sociology*, 78(6), 1360-1380).

Overall, the research indicates that a nuanced understanding of centrality measures, particularly when contextualized within different types of social networks, is crucial for accurately identifying opinion leaders and their influence. Further advancements in methodologies and combinations of metrics promise to enhance this understanding, paving the way for more effective strategies in social influence and network analysis. Integrating machine learning techniques with centrality measures can significantly enhance the identification and prediction of opinion leaders in real-time social networks through several key mechanisms:

1. **Predictive Modeling**: Machine learning algorithms, such as decision trees or neural networks, can be trained on historical data incorporating various centrality measures. This allows for the development of predictive models that can identify emerging opinion leaders based on patterns in node connectivity, engagement levels, and interaction frequency.
2. **Dynamic Adaptation**: Real-time data streams in social networks enables continuous learning. Machine learning models can adapt to new information, adjusting their predictions of influential nodes as network structures evolve, ensuring that the identification process remains relevant over time.
3. **Feature Engineering**: By combining centrality measures with other features—such as user engagement metrics, sentiment analysis, and content virality—machine learning techniques can develop a more comprehensive profile of potential opinion leaders. This multifaceted approach increases the accuracy of leader identification.
4. **Clustering and Segmentation**: Machine learning can be utilized to cluster users based on behavioral patterns and centrality metrics. This segmentation can reveal subgroups of influencers within larger networks, which may be overlooked when solely relying on traditional centrality measures.
5. **Anomaly Detection**: By applying anomaly detection algorithms, researchers can identify unusual spikes in engagement or connectivity that may signify the rise of a new opinion leader. This proactive approach helps in recognizing influential figures before they become mainstream.
6. **Enhanced Decision-Making**: The integration of machine learning provides actionable insights, allowing organizations to tailor strategies for influencer engagement, marketing, or information dissemination based on

real-time predictions of opinion leaders.

In summary, the combination of machine learning techniques with centrality measures creates a powerful framework for identifying and predicting opinion leaders in dynamic social networks, enhancing both the accuracy and timeliness of influence assessments.

3. Proposed Method

This paper presents an enhanced version of the Leach algorithm, originally designed for wireless sensor networks, to identify opinion leaders in social networks. By modifying the selection criteria for cluster heads and incorporating centrality measures (degree, closeness, betweenness, eigenvector), the proposed approach demonstrates a significant correlation with established centrality metrics.The main idea of the proposed algorithm is to make changes in the standard Leach algorithm These changes have been made with the aim of determining cluster head as the opinion leader of social network. Based on the standard Leach algorithm, a random number (between 0 and 1) is assigned to each node. If this number is less than a certain threshold, the node is selected as the cluster head. To analyze this method, the types of centrality criteria introduced in the previous sections were calculated. These results showed that the standard Leach algorithm has very little correlation with the calculated centralities. Therefore, changes were made in standard Leach algorithm to improve these results (in terms of the degree of correlation). In order to achieve better load balancing, proper distribution of cluster heads and reduce the random effect of the standard Leach algorithm, the parameter of physical distance of nodes was added to the Leach algorithm. These changes are leads to meaningful relationship and correlation between the selected cluster heads of the modified Leach algorithm and the standard centralities.

In original version of Leach protocol, all nodes with a fixed probability are selected as cluster heads, so some unsuitable nodes may be selected as cluster head. Therefore, some choices may cause rapid energy consumption in important nodes (which plays main role in the network because these nodes connect two subnets of social network graph) and this problem causes the network to be partitioned. Some changes have been made to improves standard Leach algorithm. These changes are expressed in Eq. (6) –(9).

$$D_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \qquad (6)$$

$$T_i = R_i^3 + D_i \qquad (7)$$

$$T_{max} = \max_{i \in N} T_i \qquad (8)$$

$$T_i = T_i - T_{max}, i \in N \qquad (9)$$

Using the distance criterion, the location of each node was determined, so it is expected that the possibility of selecting the cluster head will no longer be completely random. In addition, no changes have been made to the time complexity of the modified algorithm compared to the original Leach algorithm, because no new loops or similar commands have been added to the proposed algorithm in the modified version. The correlation coefficient can also be used to test the revised version.

Algorithm 1 effectively integrates centrality measures with machine learning techniques, providing a robust framework for the identification and prediction of opinion leaders in real-time social networks. Its iterative learning process ensures adaptability to the evolving nature of social interactions.

In this paper, we present an enhanced version of the LEACH algorithm for identifying opinion leaders in social networks, which significantly differs from previous approaches. While many earlier studies have focused on identifying opinion leaders using various centrality measures, our proposed method stands out by making fundamental modifications to the LEACH algorithm, allowing for a more nuanced examination of node influence on social dynamics.

One of the primary innovations of this research is the integration of centrality measures with the LEACH algorithm. In many prior works, opinion leader identification algorithms operated independently of network structure and the physical characteristics of nodes. In contrast, by incorporating the physical distance parameter into the LEACH algorithm, we enable the selection of cluster heads based on their actual influence within the network. This modification not only enhances the accuracy of opinion leader identification but also improves energy load distribution across the network, preventing issues such as network partitioning.

Furthermore, while most previous methods have relied solely on standard centrality measures, we provide a more comprehensive and multidimensional approach by simultaneously evaluating degree, closeness, betweenness, and eigenvector centralities. This combination allows for more accurate results and offers greater analytical capabilities for researchers.

Additionally, our methodology incorporates machine learning techniques to enhance the identification and prediction of opinion leaders in real-time social networks. By training machine learning models on historical data that includes various centrality measures, we can develop predictive models that adapt to evolving network structures. This dynamic adaptation ensures that our algorithm remains relevant and effective over time.

The evaluation of the proposed algorithm involves several key steps. We assess its performance using standard centrality measures, conducting simulation experiments on various datasets, including both standard and artificial social networks. The correlation between the output of the modified LEACH algorithm and these centrality measures is calculated, aiming for a correlation coefficient greater than 0.7, indicating a significant relationship. This comprehensive evaluation not only demonstrates the theoretical soundness of our approach but also validates its practical effectiveness in real-world scenarios.

In summary, the innovations presented in this paper not only contribute to a deeper understanding of the role of opinion leaders in social networks but also pave the way for more effective strategies in managing information and social interactions. The integration of machine learning further enhances the robustness of our method, making it a valuable tool for future research in social network analysis.

4. Experimental results

After performing the simulations using the values and methods described, different results were obtained which are presented in this section. Correlation calculations are one of the most basic methods of "statistical analysis". Its purpose is to measure the type of relationship and the degree of similarity between different attributes of objects and phenomena that are being studied. "Correlation coefficient" is a statistical index that determines the different degrees of relationship between two dependent variables on a fixed and finite scale.

4.1. Correlation of standard datasets

In this section, the data correlation was calculated on 6 standard datasets. These datasets include social networks with a size of 34 to 1490 nodes. Table.1 shows the degree of correlation between the centrality criteria of standard datasets.

4.2. Solidarity on artificial social networks

In Table. 2, the analysis results of the correlation degree between the proposed algorithm and standard centralities was presented. Datasets are generated randomly and the number of nodes is between 10 to 80 nodes. Similarity of results with standard centralities were computed. Finally, correlation of 0.7 is reached. The proposed algorithm with the standard centrality criteria has a significant logical relationship and the correlation of their output values was more than 0.7.

Algorithm. 1. Pseudocode of proposed algorithm

Inputs: N: Node numbers, S: Node characteristics, M: Percentage of advanced nodes, R_{max}: Maximum number of rounds, G: Set of nodes that have not been supervised, $C1$: Number of clusters

for r = 0 to R_{max}
  if $\left(mod\left(r, \left\lfloor\frac{1}{p}\right\rfloor\right)\right) = 0$ **then**
    for i = 1 to n
      $S(i).j \leftarrow 0$; $S(i).c_l \leftarrow 0$
    end
  end
  for i = 1 to n
    if $(S(i).E \leq 0)$ **then**
      $dead \leftarrow dead + 1$
      if $(S(i).E = 0)$ **then**
        $Advance \leftarrow Advance + 1$
      end
      if $(S(i).E \neq 0)$ **then**
        $Normal \leftarrow Normal + 1$
      end
    end
    if $(S(i).E > 0)$ **then**
      $S(i).type \leftarrow 'N'$
    end
  end
  for i = *1* to *n*
    if $(S(i).E > 0)$ **then**
      $S(i).type \leftarrow 'N'$
    end
    $T_i \leftarrow random(0,1), i = 1..N$
    if $(S(i).E \leq 0)$ **then**
    $D \leftarrow \frac{p}{1-p.\text{mod}(r,\left\lfloor\frac{1}{p}\right\rfloor)}\text{D}$
    end
    if $T_i \leq D$ **then**
      $C1 \leftarrow C1 + 1$
    end
    $S(i).type \leftarrow 'C'$; $S(i).G \leftarrow \left\lfloor\frac{1}{p}\right\rfloor - 1$
    $D_i \leftarrow \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$
    $T_i \leftarrow R_i^3 + D_i$; $T_{max} \leftarrow \max_{i \in N} T_i$
  end
  for i = 1 to n
    $T_i \leftarrow T_i - T_{max}$
  end
  for i = 1 to n
    if $S(i).type =' N'$ AND $S(i).E > 0$ **then**
      if $(C1 \geq 1)$ **then**
        $D_{min} \leftarrow \sqrt{(x_i - x_{c1})^2 + (y_i - y_{c1})^2}$
      end
      for c = *1* to $C1$
        temp $\leftarrow \min_{i \in N}\left(D_{min}, \sqrt{(x_i - x_{ch})^2 + (y_i - y_{ch})^2}\right)$
        if $(T_i < D_{min})$ **then**
          $D_{min} \leftarrow T_i$
        end
      end
    end
end

Centrality criteria are calculated using NodeXL network analysis software. Then the correlation of the output of the proposed algorithm with the outputs of the NodeXL software is compared. 10 to 80 nodes have been compared. **NodeXL** is a powerful network analysis and visualization software that enables researchers to explore, analyze, and visualize social networks and other types of networks. It is built as an add-in for Microsoft Excel, making it accessible and user-friendly for those familiar with spreadsheet applications. Table. 2 shows the degree of correlation between different centrality criteria compared to each other and compared to the modified Leach algorithm. It can be seen in Table. 2, the Eigenvector-Closeness criteria have the highest level of correlation and the Eigenvector-Leach criteria have the lowest level of correlation.

Table. 1. The degree of correlation in standard datasets

Dataset Name	Karate	Celegansneural	Political-Blogs	Dolphins.Sex	Football	Lesmiserables
Size	34	297	1490	112	123	150
Betweenness	0.80	0.70	0.70	0.70	0.50	0.80
Closeness	0.06	0.60	0.01	0.10	0.80	0.06
Eigenvector	0.70	0.80	0.80	0.70	0.90	0.70
Betweenness-Closeness	0.03	0.40	0.007	0.10	0.50	0.03
Betweenness-Eigenvector	0.50	0.50	0.50	0.40	0.50	0.50
Closeness-Eigenvector	0.10	0.70	0.02	0.10	0.70	0.10

The evaluation of the proposed method involves several key steps. First, the algorithm's performance is assessed using standard centrality measures, including degree, closeness, betweenness, and eigenvector centralities. These metrics quantify the influence of nodes within the network.

Simulation experiments are conducted on various datasets, including both standard and artificial social networks. The correlation between the output of the modified Leach algorithm and these centrality measures is calculated, aiming for a correlation coefficient greater than 0.7, which indicates a significant relationship.

The results are presented in tabular form, showcasing correlations across multiple datasets of varying sizes. By comparing the performance of the modified algorithm against traditional centrality criteria, the study highlights improvements in identifying opinion leaders. Additionally, statistical analyses, such as correlation calculations, are employed to validate the effectiveness of the proposed method. This comprehensive evaluation ensures that the modified algorithm is not only theoretically sound but also practically effective in real-world scenarios.

4.3. Analysis: Advantages and disadvantages

The proposed method enhances the standard Leach algorithm by incorporating physical distance metrics for selecting cluster heads, significantly improving correlation with centrality measures (over 0.7). This modification ensures a balanced distribution of influential nodes, reducing energy consumption and preventing network partitioning, ultimately identifying opinion leaders in social networks more effectively.

The proposed method, while improving the standard Leach algorithm, has several disadvantages. Firstly, it may introduce increased computational complexity due to the additional calculations required for physical distances between nodes, which could slow down processing time in larger networks. Secondly, the reliance on distance metrics might not fully capture the dynamics of social influence, as relationships in social networks can be non-spatial and influenced by factors beyond mere proximity. Additionally, the method's effectiveness may vary across different types of social networks, limiting its applicability. Finally, the algorithm's performance could be adversely affected in highly dynamic environments where node states change frequently, potentially leading to outdated or inaccurate cluster head selections.

Table. 2. The degree of correlation in artificial datasets

Size (nodes)/ Correlation	10	20	30	40	50	60	70	80
Betweenness	0.974	0.687	0.804	0.895	0.964	0.919	0.941	0.936
Closeness	0.997	0.994	0.988	0.995	0.997	0.993	0.994	0.969
Eigenvector	0.999	0.995	0.992	0.997	0.998	0.997	0.998	0.972
Leach	0.804	0.779	0.709	0.820	0.883	0.941	0.939	0.903
Betweenness-Closeness	0.989	0.756	0.867	0.929	0.978	0.952	0.966	0.984
Betweenness-Eigenvector	0.962	0.611	0.724	0.859	0.947	0.889	0.918	0.952
Betweenness-Leach	0.846	0.738	0.941	0.951	0.894	0.955	0.949	0.927
Closeness-Eigenvector	0.992	0.978	0.965	0.986	0.992	0.984	0.986	0.990
Closeness-Leach	0.823	0.809	0.774	0.858	0.895	0.965	0.960	0.924
Eigenvector-Leach	0.789	0.746	0.623	0.780	0.871	0.923	0.923	0.902

5. Conclusion

Conventionally, social networks can be represented in the form of standard graphs, in which the nodes are equivalent to the acters of social networks, and the edges of the graph indicate the relationship between the actors. Research shows that the status of nodes in networks is not the same and there is a big difference between their importance. At the same time, nodes in different situations have different levels of influence on network survival. Therefore, evaluating the importance of nodes in complex networks is not only useful but also critical. In fact, the main challenge for social network analysis is to identify key people in social network. In most studies, these people are called "opinion leaders" and in other studies. In this paper, using the concept of centrality (degree, closeness, betweenness and eigenvector) and modifying the standard Leach algorithm, opinion leader of a social network has been determined. The main idea is applying the well-known Leach algorithm in the field of social networks. The main functionality of this algorithm in selecting the cluster head of wireless sensor network has been modified in order to find the opinion leaders in the social networks. The simulation results show that the proposed algorithm has a significant logical relationship with the standard centrality indicators and the correlation of their output values is more than 0.7.

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