Design a Gaussian mixture-based clustering model for enhancing accuracy and robustness in smart homes

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ABSTRACT

Nowadays, smart homes have become quite complicated systems. Thus, an appropriate technique for controlling all those devices is necessary, especially considering that certain nodes are likely to be broken. In that connection, we have proposed two algorithms related to Gaussian mixture models (GMM): GMM equal and GMM unequal. They were compared with graph neural network (GNN) equal, GNN unequal, and the LucasWheel algorithms. The peculiarity of the GMM equal algorithm consists in the fact that all clusters should have similar sizes and shapes, which is quite useful for routing and balancing purposes, while the clusters in the GMM unequal algorithm can have various sizes and shapes depending on the data distribution. All five models were analyzed using 843 nodes, where failure rates ranged from zero to fifty percent. The surprising outcome of this analysis is that GMM equal performed better than the other four models in every aspect. Efficiency was steady and steadily increased in accordance with the rising failure rate. The Wiener index gradually fell from its initial value to nearly zero, suggesting a dense connection among the nodes and an evenly spread-out network. Furthermore, GMM equal attained the highest modularity among the five models at every failure level. In combination, these results indicate that GMM equal is the most balanced topology, with the best balance between reliability, efficient communication, and scalability when applied to the internet of things and smart homes.

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1. INTRODUCTION

The increasing complexity of smart home environments requires efficient and effective network clustering strategies, which are capable of maintaining their performance even in the event of node failures. This paper proposes two new clustering models, Gaussian mixture models (GMM) equal and GMM unequal, based on GMM, and compares them with graph neural network (GNN) equal, GNN unequal, and the Lucas Mesh topology. Maintaining the connectivity in a smart home internet of things (IoT) network, even when nodes fail randomly, is not an insignificant task. We considered the combination of Lucas number theory and trimet graph optimization, which produces graphs/topologies that are more fault-tolerant than the standard clustering or mesh algorithms. In our earlier simulations, Lucas-TGO performed 9-12 rounds of keeping the network running compared to 6-8 rounds in standard models [1]. This difference helped us realize that there was scope for the application of number theory in telecom, healthcare, and industry IoT. When nodes are grouped by their structural properties, the size and density of clusters start to impact all aspects of connectivity, communication, and how vulnerable they are when things go wrong [2]. Low-density graphs make structure more visible and allow for easier isolation of effects as they are sparser. Medium-density configurations try to balance efficient communication and hub resilience. High-density graphs illustrate the risks of having all eggs in one basket [3]. We intentionally chose the Lucas-based algorithm as the cluster sizes are based on Lucas sequencing; therefore, the sizes are heterogeneous, which looked promising for redundancy and scalability. Color differentiation and spring layout algorithms were used for visualization as they are simple to evaluate aspects like structure and robustness [4]. The idea for the adaptive sampling using Lucas sequencing came up after we realized that the mathematical properties could help us optimize sampling intervals.

GNN equal clustering attempts to divide the nodes such that their sizes are equal. When training, the constraints or regularizations are made strict or hardcore to ensure that they learn to balance the assignments even if they are dealing with local densities that are not uniform or equal [5]. This is essential for load balancing in distributed systems or community detection in social networks. The main idea is to keep the cardinality of the clusters homogeneous so that no one cluster takes up all the nodes [6]. Figure 1 shows GNN equal fixed-size clustering on a graph where each cluster had a target of 100 nodes each.

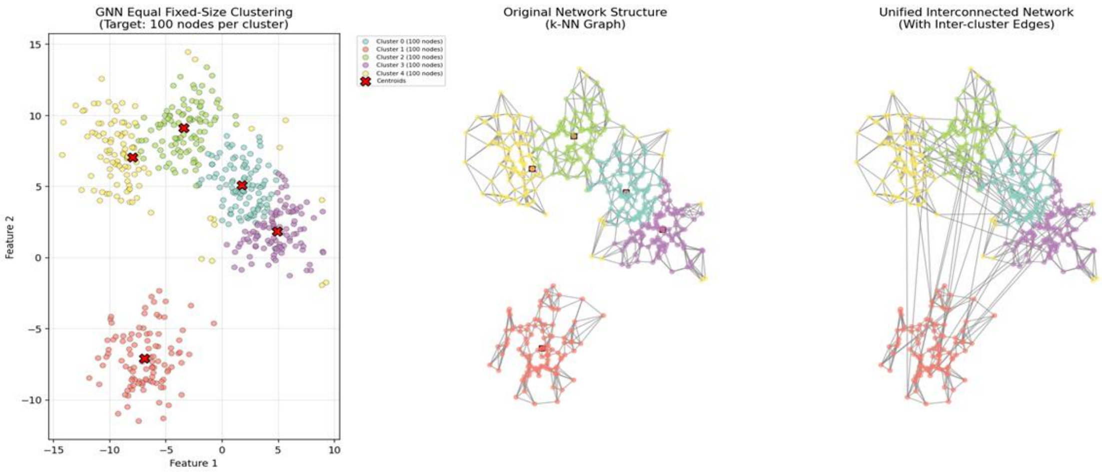

Figure 1. GNN equal clustering: the even split can be observed

On the left is the feature space, which has five clusters with 100 nodes each, so that they are perfectly balanced. The centers of each cluster, i.e, the centroids of each cluster, are marked with black X, and the cluster head of each of the cluster is circled with red. As seen, the clusters are well separated with very little overlap. This revealed that the partition worked better than we expected it to work. On the right is the original graph for the k-nearest neighbor (kNN) algorithm and the interconnected network. As seen, the cluster boundaries are preserved while enhancing connectivity [7]. This visualization shows that the GNN-based algorithms perfectly achieve size balance while effectively optimizing the network topology by simultaneously considering the local clustering objectives and global connectivity patterns.

GNN unequal clustering is the exact opposite of GNN equal, in the sense that there is no constraint on the distribution of the nodes. The clusters will be of varying sizes and shapes, as the algorithm is simply following the lead of the graph. This allows us to identify clusters of all sizes and shapes, small and tight, to large and loose, within the same graph [8]. Look at the left panel of Figure 2, we have five clusters, with sizes ranging from 58 to 276. The geographical layout is based on actual data density, not on the size constraints. The right panels illustrate the hidden connectivity beneath the surface. The large cluster is very tightly connected internally, and the smaller ones are very tightly connected, with careful bridges between them. This solved our concern about whether GNN clustering with no balancing terms could identify hidden community structures [9].

In Lucas mesh clustering builds topology from the Lucas number sequence defined by the recurrence relation, as the sequence dictates everything, like the number of clusters to a layer, the number of nodes on each concentric ring, etc. The relationships are dispersed around a central node like a wheel [10]. We selected this model since fault tolerance analysis is easier due to the deterministic path lengths. The multi-layer hierarchical model is illustrated in Figure 3. The red nodes indicate the cluster heads or the critical hubs. The right-hand figures depict the entire network, the consolidated form, with redundant paths all through, which will be handy in case of node failure [11].

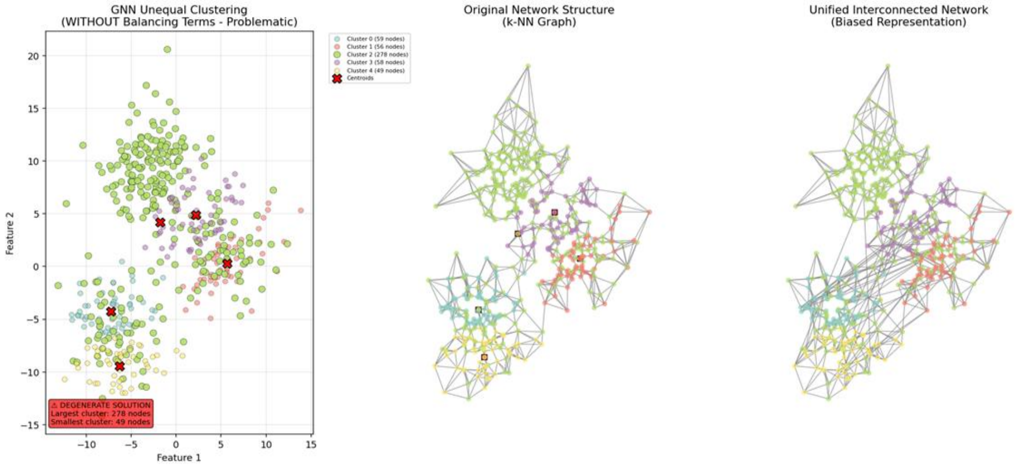

Figure 2. GNN unequal clustering: the split naturally varies

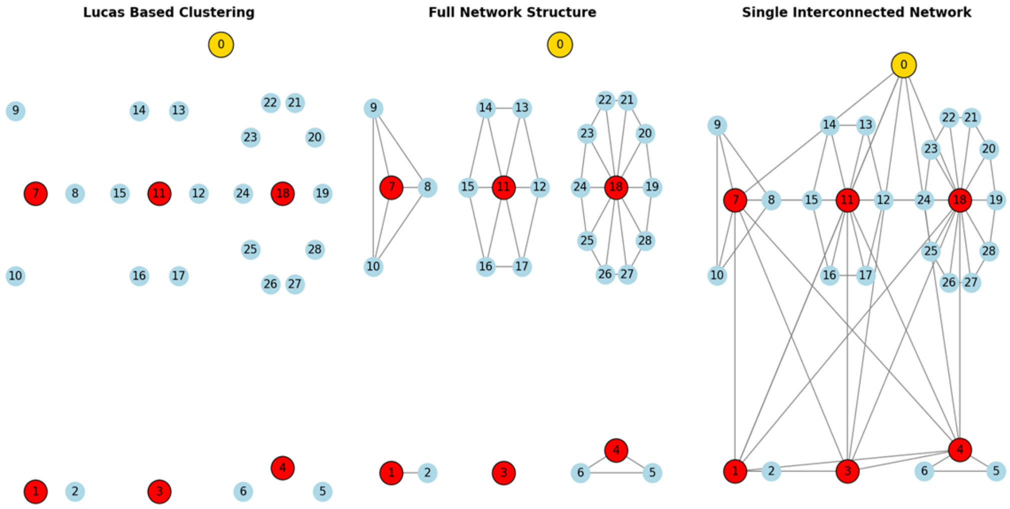

Figure 3. Lucas-based unequal clustering: the split is organized in layers

2. LITERATURE SURVEY

In the evolution of new technologies, communication networks are constantly changing for better efficiency, scalability, and resiliency, which are the recurring patterns of graph theory. In the paper by Rajana and Amiripalli [1], the authors used the Lucas numerical sequence and trimet graph optimization for IoT network resiliency for smart home IoT networks. Their mesh network, based on the Lucas numerical sequence, performed better with random node failures. In another paper, Chen and Zhang [2] investigated the mathematical foundations of clustering theory, specifically GMM, minimax lower bounds, and algorithms. We extended our work based on some of the concepts presented. However, the homogeneous properties of covariance are not valid for random node failures, which might limit the direct application for IoT networks with disrupted clusters.

In our study, this was reflected in the low fault tolerance of GNN unequal: less than 0.35 and only up to 20 iterations. Song and Zhang's [4] introduced wheel and star architectures combining wavelength division multiplexing and wireless protection. The use of ring topology for interconnections, along with a star topology for connectivity, ensured high reliability, minimum latency, scalability, and AI-assisted fault recovery. Tsitsulin *et al.* [8] took unsupervised graph neural network pooling to the next level using modularity optimization. Their DMoN module was effective on clusters of equal size. Their study also showed the limitations of GNN clustering on clusters of unequal size: the importance of the robustness of the algorithm was more significant than previously assumed. Kirmani *et al.* [12] provided an exhaustive overview of IoT-based smart grid systems. Their work included three-tiered architecture, cloud architecture, communication systems, and security systems utilizing blockchain and AI.

The authors Karakoc and Konar [13] used complex network theory for global trade networks with star topology, scale-free topology, and ring topology. They found core-periphery structures and lattice structures from the tradeoff between efficiency and resilience. Their work is insightful, but trade networks behave differently from IoT networks. Nelson *et al.* [14] proved the applicability of the mesh topology with low-power Zigbee networks for environmental monitoring. "Self-healing, cost-effective, and reliable data acquisition." However, the network size was limited to fewer than 50 nodes. Nurlan *et al.* [15] critically analyzed the interfaces for WSN and WMNs in terms of performance, protocols, and security and privacy. AI and ML play an important role in this area. However, there was no quantification of the resiliency. Ompal *et al.* [16] provided an overview of the integration of star topology, mesh topology, and cluster tree topology with FPGA and IEEE 802.15.4. Their focus on internode communication, energy efficiency, and AI-based optimization pointed forward. However, they did not consider node failures. What is missing across most of these references is an honest discussion of what failed or underperformed. We tried to address that in our work.

3. PROPOSED MODEL

GMM equal and GMM unequal clustering strategies propose a different approach in clustering the cluster sizes with uniform across networks in the equal case and variable in the unequal case.

3.1. GMM equal

GMM equal clustering forces each Gaussian component to share an identical covariance structure and pushes balanced membership distribution Figure 3. Each cluster becomes spherical or identically oriented ellipsoidal. This works when you assume that the groups have a similar density and space. We have tested it with synthetic data for three components with a spherical covariance and with three well-separated equal-size clusters [12]. The result came out with a uniform shape and with a similar distribution of points. Assuming that all the components have equal weights while initializing presupposes that the groups have a balanced composition, which prevents a dominant cluster from taking over the assignments [17]. To be honest, this works best when you specifically want homogeneity between clusters [13]. We have conducted extensive analysis with a network dataset, which has four clusters, with exactly 100 nodes in each. The left panel in Figure 4 shows the 2D feature space, with yellow, green, purple, and blue clusters, with black X's for the centroids, and red for the cluster heads [14]. Some probabilistic overlap, which we wanted, is shown with the use of a GMM. The right panels show the entire network and the unified version with interconnected networks. Figure 5 illustrates the flowchart, and Tables 1 and 2 show the notation table for GMM.

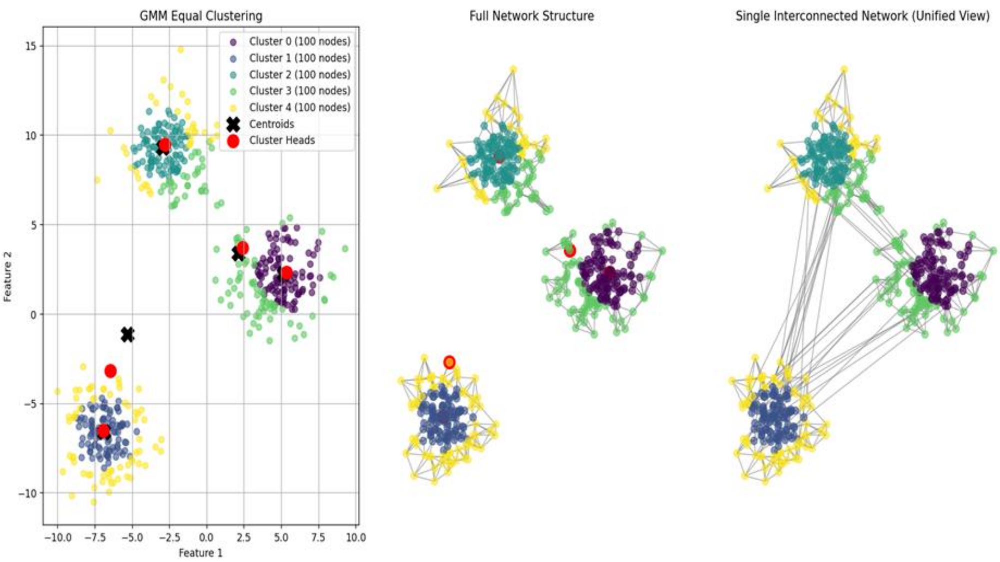

Figure 4. Proposed model of GMM equal visualization: clustering

3.2. GMM unequal

This flexibility is particularly useful for heterogeneous data where the clusters vary in terms of spread and density [15]. As shown in our experiments, this flexibility led to one of the clusters containing more than 30. Figure 6: unexpected density concentration of Cluster 1 and subsequent rapid increase in betweenness centrality. Left: 2D feature space showing the distribution of the four clusters with varying sizes. Clustering results: Cluster 0: 52 nodes (blue). Cluster 1: 166 nodes (teal). Cluster 2: 90 nodes (yellow). Clusters 3 and 4: 115 and 77 nodes (green and purple). Right: complete network and combined view. The unequal clustering resulted from the heterogeneous data and is expected to be natural [16]. This imbalance proves the effectiveness of GMM in dealing with real-world situations where natural groupings are not always balanced. As shown by the distinct boundaries of the clusters with prominent centroids and heads of the clusters, the algorithm was successful in discovering structural patterns within the data set. The panels on the right portion of the graph show additional information regarding the structure of the network, which can be used to further understand the data set presented [18]. The "Full Network Structure" of Figure 6 shows the complex interconnectedness of the data set, with the largest cluster (Cluster 1) showing dense connectivity within the group while establishing strategic connections with other clusters [19]. The single interconnected network (Unified View)" shows the global structure of the data set. Figure 7 shows its flowchart, demonstrating that the unequal clustering is a natural representation of the hierarchical structure of the data set without compromising the overall cohesion of the network architecture.

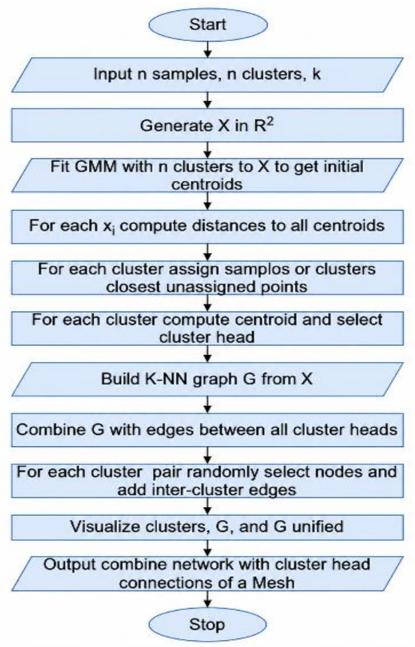

Figure 5. Proposed model of GMM equal visualization: flowchart

Table 1. Notation table for GMM equal

Symbol	Description
n	Total number of data points (samples)
$n_{samples}$	Number of data points generated (e.g., 500)
X	Data matrix of shape (n,2), where each row is a two-dimensional data point
$n_{clusters}$	Number of clusters (e.g., 5)
k	Number of nearest neighbors for network construction (e.g., 5)
GMM	Gaussian mixture model used for clustering
μ_j	Initial centroid of cluster j as determined by the GMM
fixed_cluster_size	Number of points per cluster for equal-size assignment ($n/n_{clusters}$)
labels	Cluster assignment vector for all data points
centroids	Array of recalculated centroids after equal-size assignment
Cluster_heads	Indices of points closest to each centroid (designated as cluster heads)
Cdist (X, Y)	Pairwise distance matrix between points in X and Y
G	kNN network graph
$G_{combined}$	Network graph with additional edges connecting all cluster heads
$G_{unified}$	Network graph with supplementary inter-cluster edges
pos	Dictionary mapping node indices to their 2D (x, y) coordinates for visualization
unique_labels	Unique cluster labels present in the data
cluster_counts	Dictionary of node counts per cluster
inter_edges_per_pair	Number of inter-cluster edges added between each pair of clusters
newly_added_inter_cluster_edges	List of new inter-cluster edges introduced in the unified network

Table 2. Notation table for GMM unequal

Symbol	Description
n	Total number of data points (samples)
nsamples	Number of data points generated (e.g., 500)
X	Data matrix of shape (n,2), where each row is a two-dimensional data point
nclusters	Number of clusters (e.g., 5)
k	Number of nearest neighbours for network construction (e.g., 5)
GMM	Gaussian Mixture Model used for clustering
µj	Initial centroid of cluster j as determined by the GMM
distances	Pairwise distance matrix between data points X and centroids µj
labels	Cluster assignment vector for all data points
centroids	Array of recalculated centroids -size assignment
Cluster_heads	Indices of points closest to each cluster centroid µj (cluster heads)
Cluster_nodes_indices	List of arrays, each containing the indices of nodes belonging to cluster j
G	kNN network graph constructed from X
Gcombined	Network graph G with additional edges connecting all cluster heads
Gunified	Network graph G with supplementary inter-cluster edges
pos	Dictionary mapping node indices to their two-dimensional coordinates for visualization
cluster_counts	Dictionary of node counts per cluster
inter_edges_per_pair	Number of inter-cluster edges added between each pair of clusters
newly_added_inter_cluster_edges	List of new inter-cluster edges introduced in the unified network

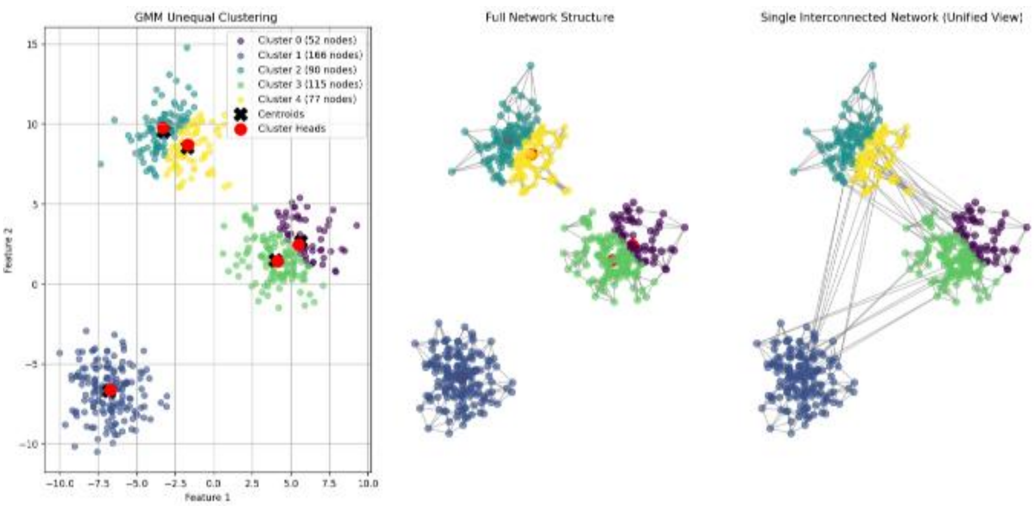

Figure 6. Proposed model of GMM unequal visualization: clustering

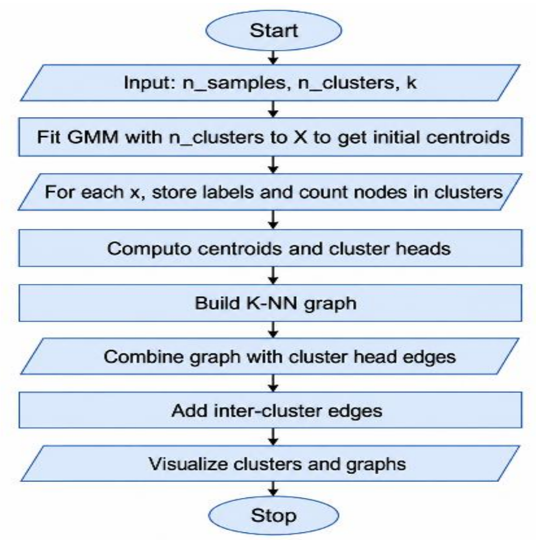

Figure 7. Proposed model of GMM unequal visualization: flowchart

The proposed Algorithm 1 GMM equal begins by randomly deploying n_samples sensor nodes across a two-dimensional region, after which a GMM is fitted to the node coordinates to estimate probabilistically informed initial centroids, offering a statistically superior alternative to conventional random seeding. Each node then computes its Euclidean distance to all centroids, and a balanced partitioning strategy assigns exactly [n_samples/n_clusters] nodes to each cluster by iteratively selecting the closest unassigned nodes, thereby ensuring a uniform energy load distribution across the network. Within each cluster, the centroid is recomputed as the mean position of assigned nodes, and the node lying closest to this centroid is elected as the cluster head (CH), designated to perform local data aggregation and inter-cluster forwarding. A kNN graph G is subsequently constructed over all nodes to establish local communication links reflecting physical proximity, upon which a full mesh overlay. $G_{combined}$ is formed by interconnecting all CHs, enabling direct single-hop communication between any two clusters and significantly reducing routing overhead. To further enhance network resilience, stochastic inter-cluster bridge edges are introduced by randomly selecting node pairs from neighboring clusters and connecting them, yielding the final unified graph $G_{unified}$, whose topology is then visualized to validate cluster formation, local connectivity, and inter-cluster mesh structure, making the overall framework well-suited for energy-constrained WSN and IoT network design.

Algorithm 1. GMM equal

```
Input: n_samples, n_clusters, k
Output: Combined network with cluster head connections of a Mesh
Step 1: Start
Step 2: Generate X = {x_1 , ..., x_n} in R^2
Step 3: Fit GMM with n_clusters to X → initial_centroids
Step 4: For each x_i:
     Compute distances to all centroids
Step 5: For each cluster j:
     Assign n_samples/n_clusters closest unassigned points to cluster j
Step 6: For each cluster j:
     centroid_j = mean (points in cluster j)
     cluster_head_j = argmin_x ||x - centroid_j||
Step 7: Build k-NN graph G from X
Step 8: G_combined = G + edges between all cluster heads
Step 9: For each cluster pair (i, j):
     Randomly select nodes from i and j
     Add inter-cluster edges in G_unified
Step 10: Visualize clusters, G, and G_unified
Step 11: Stop
```

The Algorithm 2 GMM unequal begins with the random deployment of n_samples sensor nodes in a two-dimensional region. Subsequently, a GMM was fitted to the node coordinates, generating probabilistically informed initial centroid positions that more accurately reflect the spatial distribution of the nodes than traditional seeding methods. At this point, an initial cluster label is assigned to each node based on the output of the GMM, and the number of nodes per cluster is recorded to quantify the initial distribution before rebalancing. Then a balanced partitioning step is performed in which each cluster is assigned exactly [n_samples/n_clusters] nodes by iteratively selecting the closest unassigned nodes. This ensures uniform cluster sizes and similar energy load distribution over the network. $CH_j = \arg\min_x \|x - centroid_j\|$. The centroid is then recalculated as the mean position of all assigned nodes, and the node closest to the refined centroid is elected as the CH. The CH is responsible for local data aggregation and inter-cluster forwarding. A kNN graph G, is then constructed over all nodes to model local communication links, and a full mesh overlay $G_{combined}$ is formed by interconnecting all CHs for direct single-hop inter-cluster communication. To further improve network resilience, we introduce all possible edges between randomly chosen node subsets from each pair of neighboring clusters and store these newly added inter-cluster edges explicitly in newly_added_inter_cluster_edges for traceability, yielding the final unified graph $G_{unified}$. The resulting topology is then visualized with cluster annotations, centroids, and CH designations to enable rigorous validation and performance analysis in WSN and IoT research contexts.

Algorithm 2. GMM unequal

```
Output: Combined network with cluster head connections of a Mesh
Step 1: Start
Step 2: Generate X = {x_1 , ..., x_n} in R^2
Step 3: Fit GMM with n_clusters to X → initial_centroids
Step 4: For each x_i :
     Store in labels; count nodes in each cluster
Step 5: For each cluster j:

     Assign n_samples/n_clusters closest unassigned points to cluster j
```

```
Step 6: For each cluster j:
     centroid_j = mean (points in cluster j)
     cluster_head_j = argmin_x ||x - centroid_j||
Step 7: Build k-NN graph G from X
Step 8: G_combined = G + edges between all cluster heads
Step 9: For each cluster pair (i, j):
     Randomly select nodes from i and j
     Add all possible edges between these nodes in G_unified
    Store new edges in newly_added _inter_cluster_edges
Step 10: Visualize:
    Clusters with node counts, centroids, and cluster heads
    Full k-NN network structure
   Unified network with inter-cluster edges
Step 11: Stop
```

4. RESULT AND DISCUSSSION

Network science evaluation has resulted in the creation of tools that enable us to measure the performance of an algorithm in three overlapping dimensions: structural robustness, communication efficiency, and robustness against failure [20]. There are several metrics in each category/dimension. Structural robustness describes the extent to which the network stays connected during a disruption [21]. The number of connected components is called fragmentation [22]. The degree of redundancy of paths is measured by the average degree [23].

Clustering coefficient is a measure of local cohesion. Network density is used to measure global connectivity. Wiener index is a measure of efficiency in rerouting of paths. Communication efficiency studies the efficiency of information travel. The density of the network is negatively associated with path lengths. Betweenness centrality identifies key intermediaries whose failure propagates routing. Failure resilience combines robustness with efficiency to keep functioning in the face of progressive node failure [24]. The post-failure related components show the intensity of fragmentation. Remaining alternate paths are measured by survival of the average degree and graph density. Eigenvector centrality is used to evaluate the significance of strongly influential nodes [25]. All these metrics are indicators of network survivability across failure rates; the robustness score shown in Figure 8 revealed LucasWheel dominated all, with scores over (~46) at zero failure but declined steeply with increasing failures. GMM equal sustains better resilience than GMM unequal, while GNN equal and GNN unequal behave similarly throughout. Beyond 45% failure, all topologies converge near a score of 4 to 6, indicating that structural advantages diminish under severe node degradation. The efficiency score shown in Figure 9 revealed a gradual upward trend, as network contraction reduces average path lengths among surviving nodes. GMM equal sustains the highest efficiency throughout (~0.59 to 0.65), whereas GNN equal exhibits the steepest rise, peaking at ~0.70 at 50% failure. GMM unequal consistently records the lowest efficiency, while LucasWheel and GNN unequal follow moderate ascending trends, converging near 0.58 to 0.65 at higher failure rates. Figure 10 compares the modularity scores of five topologies across node failure rates from 0% to 50%. GNN equal achieves the highest modularity (~0.65), while GMM equal, GMM unequal, and GNN unequal maintain comparable scores between 0.56 to 0.65, all showing a slight decline as the failure rate increases. LucasWheel records a near-zero modularity across all failure conditions, confirming its hub-centric architecture lacks any meaningful community structure.

These results suggest that GMM and GNN-based topologies preserve stronger cluster organization under node failures compared to LucasWheel. Centrality Balance, shown in Figure 11, revealed the structural differences among the methods. Except at zero failure, GNN equal and GMM unequal exhibit the highest values (~0.12 and ~0.11), whereas GNN unequal starts near zero, reflecting highly skewed load distribution. All topologies drop sharply by 5% in failure and subsequently stabilize within a narrow band of 0.01–0.03, with no topology consistently outperforming others. This convergence implies that progressive node failures naturally redistribute traffic load among surviving nodes, reducing centrality imbalance regardless of the initial topology design. Failure resilience performance of all five clustering algorithms under node failures are shown in Figure 12. LucasWheel starts with a perfect score of 1.0 but degrades most severely, dropping to ~0.08 at 50% failure, making it the least fault-tolerant topology overall. GMM equal exhibits the strongest resilience throughout, declining gradually from ~0.88 at 10% to ~0.39 at 50% failure. GMM unequal, GNN equal, and GNN unequal follow comparable descending trends, converging near 0.25 to 0.31 at 50% failure, confirming that GMM and GNN based topologies sustain better connectivity than LucasWheel under progressive node degradation.

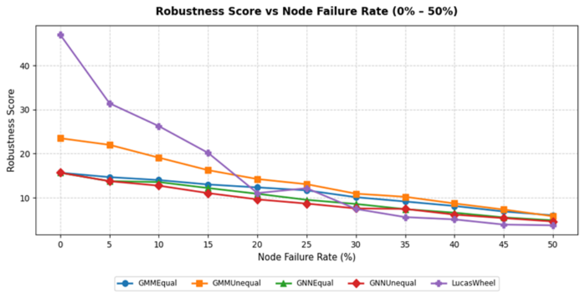

Figure 8. Robustness score performance of clustering algorithms under node failures

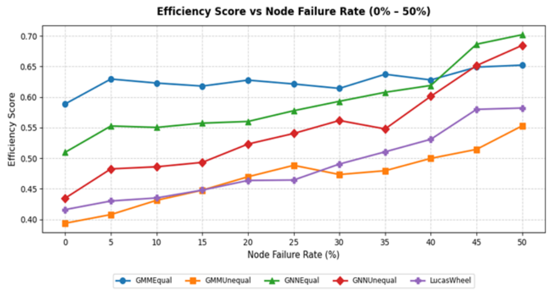

Figure 9. Efficiency score performance of clustering algorithms under node failures

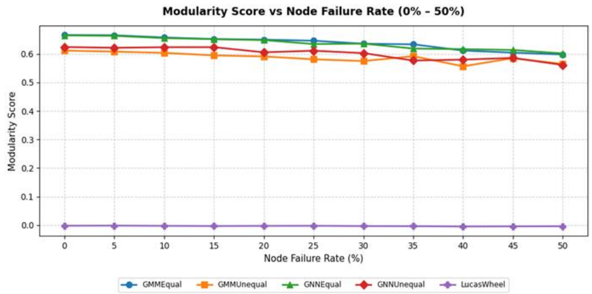

Figure 10. Modularity score performance of clustering algorithms under node failures

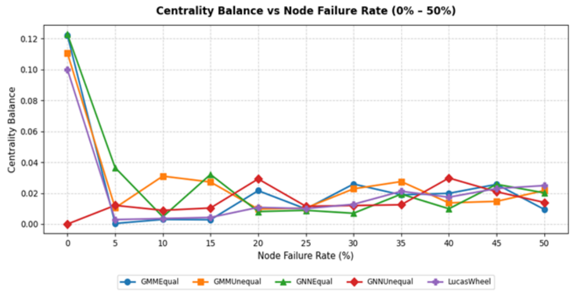

Figure 11. Centrality balance performance of clustering algorithms under node failures

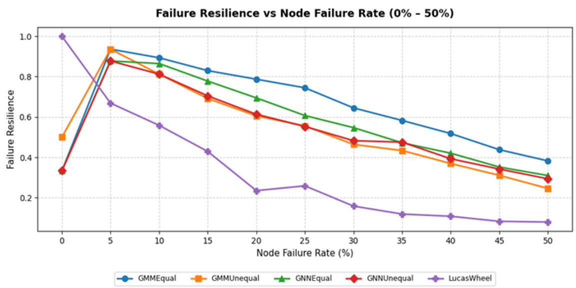

Figure 12. Failure resilience performance of clustering algorithms under node failures

5. CONCLUSION

After testing all the algorithms on 843 nodes with the failure rate of 50 percentage, the GMM equal algorithm proved the most well-rounded performer with sustaining competitive efficiency and the slowest resilience decay across all tested conditions. LucasWheel, despite its superior initial robustness, degraded sharply under progressive node failures with negligible modularity, limiting its practical applicability. GNN equal exhibited the strongest modularity and efficiency gains at elevated failure rates, while centrality balance converged across all topologies beyond critical failure thresholds. These outcomes validate that GMM, GNN based clustering frameworks are more resilient, and structurally stable, positioning GMM equal as the optimal architecture for wireless sensor network design under adverse conditions.

6. FUTURE WORK

Future research should build upon this analysis by applying the same algorithms on larger networks that surpass the size of 10,000 nodes, while considering dynamic failure scenarios such as cascading failures and adversary attacks to mimic the real-life conditions within essential systems. In addition, there is scope for studying hybrid algorithms where the resilience of GMM equal is combined with the modularity of GNN equal using ensemble learning techniques or reinforcement learning techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

To The authors declare no conflicts of interest

DATA AVAILABILITY

The data that support the findings of this study are available upon reasonable request to the corresponding author.

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