Machine Learning Approaches for Subcluster in IoT Sensor Networks with Hierarchical Clustering and Dendrograms

Fuad Bajaber[1]

[1]Department of Information Technology, Faculty of Computing and Information Technology. King Abdulaziz University, Jeddah, Saudi Arabia
Corresponding Author: fbajaber@kau.edu.sa

Abstract

This research focuses on optimizing IoT Sensor Networks (ISNs) by implementing hierarchical clustering algorithms. Traditional clustering methods often lead to imbalanced energy consumption, impacting network lifetime and performance. Our approach leverages hierarchical clustering to partition the network into a set of clusters. Each cluster has a cluster head and a set of sensor nodes. To enhance data aggregation and energy efficiency, we introduce subclustering within clusters using dendrograms. We assessed performance metrics using simulation, including energy consumption and scalability. The proposed hierarchical clustering methodology significantly improves network lifetime, energy efficiency, and data aggregation.

Keywords: IoT, Hierarchical clustering, Subclustering, Network optimization.

1. INTRODUCTION

IoT Sensor Networks (ISNs) have emerged as an essential technology with various applications, such as environmental monitoring, industrial automation, and healthcare. These networks consist of sensor nodes collaborating to collect and transmit data to a base station. However, the resource constraints of sensor nodes, such as limited energy and processing capabilities, pose significant challenges to the efficient operation of ISNs. In addressing these challenges, this paper explores hierarchical clustering algorithms applied to ISNs. This research aims to enhance energy efficiency in ISN [1-6].

Energy efficiency remains a primary concern in ISNs due to the inaccessible locations of sensor nodes. Maximizing the network's lifetime while minimizing energy consumption is essential for sustainable, long-term monitoring and data collection.

Hierarchical clustering is a powerful tool that enhances communication, reduces delays, and improves scalability in ISNs. As these networks expand to cover larger areas, the ability to scale while maintaining efficient data management and communication becomes crucial. Hierarchical structures,

by distributing the network's workload, ensure its responsiveness as it grows [7-13].

Our methodology relies on hierarchical clustering algorithms, with a focus on the complete-linkage method. Hierarchical clustering organizes sensor nodes into clusters based on their proximity and connectivity. The cluster head, a key component in this process, coordinates and manages communication within the cluster, playing a central role in data aggregation and transmission [14-20].

Furthermore, we introduce the concept of subclustering using dendrograms. Subclustering involves dividing each cluster into smaller subclusters and optimizing data aggregation within these units. Subclusters consist of at least two Subnodes, with one designated as the Subhead. Subnodes collect environmental data and transmit it to the Subhead, which aggregates the information before forwarding it to the cluster head. The cluster head further aggregates data from nodes and Subheads before transmitting it to the base station. To assess the performance and efficacy of our hierarchical clustering approach, we define metrics for evaluating energy efficiency and simulation time. These metrics are key to understanding the impact of our methodology on ISNs.

This paper investigates hierarchical clustering algorithms to address critical challenges in ISNs. Our research covers energy efficiency providing valuable insights into the design and optimization of these networks.

2. RELATED WORKS

IoT sensor networks have become essential in various fields, from environmental monitoring to industrial automation. Clustering algorithms enable efficient data gathering and management within these networks. Several clustering algorithms have been identified in the literature, each offering distinct advantages and facing specific limitations. Three essential algorithms in the context of ISNs are LEACH [21] (Low Energy Adaptive Clustering Hierarchy), PEGASIS [22] (Power-Efficient GAthering in Sensor Information Systems), and HEED [23] (Hybrid Energy-Efficient Distributed clustering)

LEACH introduced the concept of dynamic clustering, where sensor nodes take turns serving as cluster heads. This approach helps distribute energy consumption among nodes and extends the network lifetime. LEACH can prolong the network lifetime, but it struggles when dealing with the challenge of managing energy heterogeneity among nodes. HEED represents a significant improvement by incorporating an energy-aware approach. It considers the residual energy of nodes and their proximity for cluster formation. This hybrid algorithm offers cluster head selection and enhanced energy efficiency, which is particularly suitable for networks with non-uniform node distributions. PEGASIS takes a different route by forming chains of sensor nodes for data aggregation. This approach minimizes the need for long-distance radio communication, significantly reducing energy

consumption. However, PEGASIS may not be the most suitable choice for applications requiring real-time data delivery due to its primary focus on data aggregation.

Arjunan et al. [24] presents a clustering protocol to address energy efficiency and longevity in wireless sensor networks. The authors introduce an approach using the F5N algorithm to form unequal clusters. By addressing energy imbalances using the F5N algorithm, the protocol offers a solution to improve the sustainability and efficiency of sensor networks. This method accounts for both energy levels and node density when selecting cluster heads, ensuring a more balanced energy distribution and an extended network lifetime. The protocol utilizes a static method for cluster formation, where clusters are established at the beginning and remain throughout the network's operation.

The authors [25] present an approach to improving the efficiency and reliability of sensor networks. They propose an "on-demand" approach to cluster head formation, enabling clusters to adapt dynamically to network conditions. This flexibility ensures efficient energy utilization and prolongs the network lifetime. This approach allows nodes to self-organize into clusters based on their roles and proximity. It eliminates the need for a centralized controller, reducing network overhead and enhancing scalability. Furthermore, this approach presents a reliable multipath routing mechanism. This routing strategy creates multiple paths to transmit data and enhance data delivery. Although the protocol effectively balances cluster head selection, it lacks a clear mechanism for managing intra-cluster communication, especially in larger clusters. Nodes within these clusters may face increased energy consumption due to longer communication distances.

Daneshvar et al. [26] propose an approach to address the critical issue of energy efficiency in wireless sensor networks. The authors introduce a centralized cluster-based routing approach, deploying the Grey Wolf Optimizer (GWO) as the underlying optimization technique. One of the contributions of this work lies in the utilization of GWO, to optimize cluster formation and routing in sensor networks. The study effectively addresses the issue of cluster formation; however, it lacks a hierarchical mechanism that could further enhance communication efficiency. Larger clusters may experience increased communication overhead among nodes.

Sharma and Verma [27] propose the Layered Energy Balanced Unequal Clustering and Routing (LEBUCR) protocol, which addresses the challenges associated with energy imbalance in sensor networks. This protocol employs a layered clustering mechanism to form clusters with balanced energy levels. This approach mitigates the energy depletion of sensor nodes and contributes to extended network lifetime. While LEBUCR distributes clusters effectively in a layered manner, it lacks an intra-cluster hierarchy. This means all nodes within a cluster communicate directly with the cluster head.

3. ORIGINALITY

Our research evaluates the impact of subclustering within IoT Sensor Networks to enhance energy efficiency and network scalability. By leveraging hierarchical clustering algorithms and employing dendrogram based subclustering, our approach optimally partitions clusters into smaller subclusters, ensuring balanced resource distribution. This methodology extends network lifetime and reduces communication overhead, addressing limitations observed in traditional clustering approaches.

4. SYSTEM DESIGN

This section provides an overview of the methodologies and strategies employed in our approach of subclusters within IoT sensor networks by applying hierarchical clustering algorithms and dendrogram analysis.

4.1 Network Division with Complete-Linkage Clustering

The initial phase of our methodology involves partitioning the IoT Sensor Network (ISN) into clusters using the complete-linkage hierarchical clustering algorithm. Complete-linkage clustering, also known as maximum linkage clustering, is chosen for its ability to form compact and well-separated clusters by considering the maximum distance between any pair of points in different clusters. To determine the optimal number of clusters, we employ the elbow method.
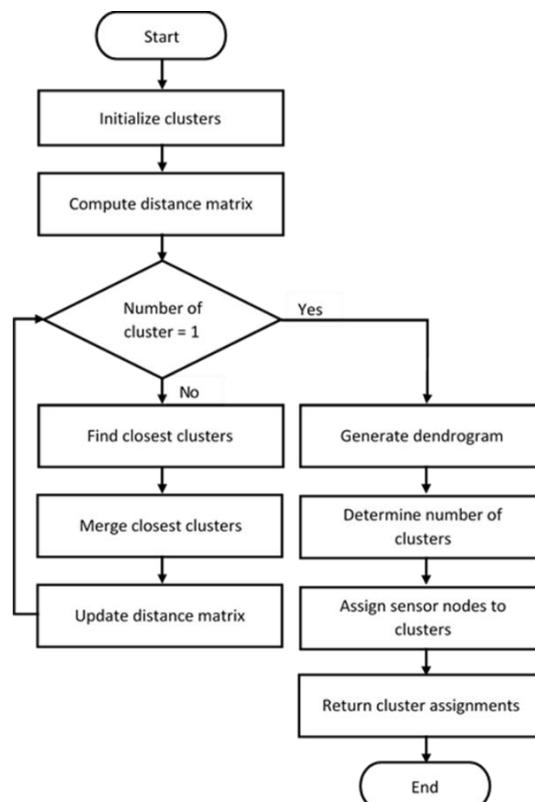

Figure 1: Hierarchical clustering

This method helps identify the point where adding more clusters does not significantly improve the network's overall performance. By optimizing the number of clusters, we ensure efficient use of resources and enhanced network performance, which are critical in ISNs where energy efficiency and data transmission reliability are essential. This process results in a set of clusters, each structured to maximize data aggregation efficiency and minimize energy consumption. The outlined procedure is illustrated in Figure 1.

1. Cluster Initialization: In this stage, clusters are created for each sensor node.

2. Distance Matrix Computation: The distance matrix is computed using the complete-linkage method, which determines the distance between clusters by considering the maximum distance between any pair of nodes from each cluster. The Euclidean distance formula is used to calculate the distance matrix (1).

$$d(n1, n2) = \sqrt{|x_1 - x_2|^2 + |y_1 - y_2|^2} \tag{1}$$

3. Merge Clusters until Only One Cluster Remains: This is the core of the hierarchical clustering process:
  - Find Closest Clusters: The algorithm identifies the two closest clusters by finding the minimum distance between clusters in the distance matrix.
  - Merge Clusters: The two closest clusters are merged into a single cluster, combining the sensor nodes from both clusters.
  - Update Distance Matrix: After merging clusters, the distance matrix is updated to reflect the changes.

4. Generate Dendrogram: A dendrogram, a tree-like diagram, is created to show the merging of clusters at each step.

5. Determine Number of Clusters: The dendrogram helps determine the number of clusters using a selected criterion such as the elbow method, which involves plotting the variance or sum of squared distances against the number of clusters.

6. Assign Sensor Nodes to Clusters: Once the optimal number of clusters is determined, each sensor node is assigned to one of the identified clusters based on their proximity or similarity.

7. Return Cluster Assignments: Finally, the algorithm returns the assignments of sensor nodes to their respective clusters, providing a partitioning of the sensor network into groups.

Overall, hierarchical clustering is an iterative process that progressively merges clusters based on their proximity until a stopping criterion is met, ultimately producing a hierarchical structure of clusters that represents the underlying relationships between sensor nodes in the network.
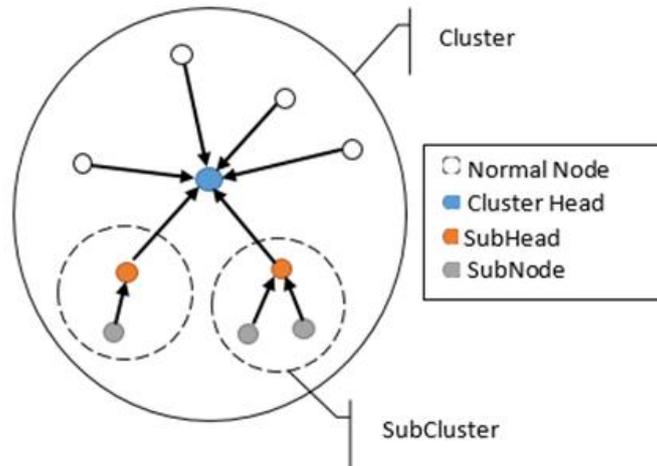
Figure 2. ISN clustering topology.

4.2 Cluster Structure

In our methodology, the ISN is structured into clusters to facilitate data communication and management. Each cluster is comprised of a designated cluster head and a set of sensor nodes called Normalnodes. A Normalnode is a regular sensor node within a cluster that performs sensing tasks. A Cluster Head is a designated node within a cluster responsible for managing communication between sensor nodes and the base station. This clustering procedure can enhance energy efficiency throughout the network.

The cluster heads play a crucial role in coordinating and managing the operations of their respective clusters. The selection of cluster heads is based on the residual energy levels of the sensor nodes. Nodes with higher energy reserves or better energy management capabilities are more likely to be assigned as cluster heads. Additionally, rotation schemes can be implemented to evenly distribute energy consumption and prevent energy depletion in a single cluster head. These schemes periodically rotate the role of cluster head among sensor nodes, ensuring a fair distribution of responsibilities.

To enable efficient communication within clusters, the cluster heads employ the Time-Division Multiple Access (TDMA) technique. TDMA allows the cluster head to allocate specific time slots to each node within its cluster for data transmission. By dividing time into slots, each node can transmit and receive data in a synchronized manner, minimizing collisions and maximizing the utilization of the available bandwidth. This synchronized communication scheme ensures that nodes within the cluster can exchange information effectively and avoid unnecessary congestion.

The TDMA-based communication employed by the cluster heads enables them to perform data aggregation efficiently. The cluster heads collect data from the Normalnodes and aggregate the collected information. The aggregated data is then transmitted by the cluster head to the base station in the network, as shown in Figure 2.

4.3 Subclustering with Dendrograms

In this phase of our clustering methodology, we implement subclustering within each primary cluster using dendrograms. A dendrogram is a tree-like diagram that records the sequences of merges or splits in hierarchical clustering. We can identify an appropriate threshold to further divide each primary cluster into subclusters by utilizing dendrograms.

The threshold (Thr) for subclustering is determined based on the sensing range of the sensor nodes, ensuring that nodes within a subcluster are within an optimal communication distance of each other. This threshold is chosen to facilitate efficient data aggregation and to enhance the reliability of data transmission within subclusters. By this way, we ensure that sensor nodes within the same subcluster can effectively communicate with minimal energy consumption, which is a critical factor in the overall performance of IoT sensor networks, as illustrated in Figure 3. Each subcluster contains a minimum of two subnodes, with one designated as the subhead for coordination, ensuring the process is efficient and well-organized, and a set of sensor nodes called subnodes. A Subnode is a sensor node that belongs to a subcluster and sends its data to a subhead instead of directly communicating with the cluster head, as listed in Table 1.

This approach enables us to create a multi-tier hierarchical structure that reduces the communication overhead and improves data aggregation efficiency. By breaking down large clusters into smaller, more manageable subclusters, we enhance the scalability of the network, allowing it to support a larger number of sensor nodes without compromising on performance. This subclustering process ensures that the network remains efficient, even as it scales up to accommodate more nodes and data aggregation tasks.
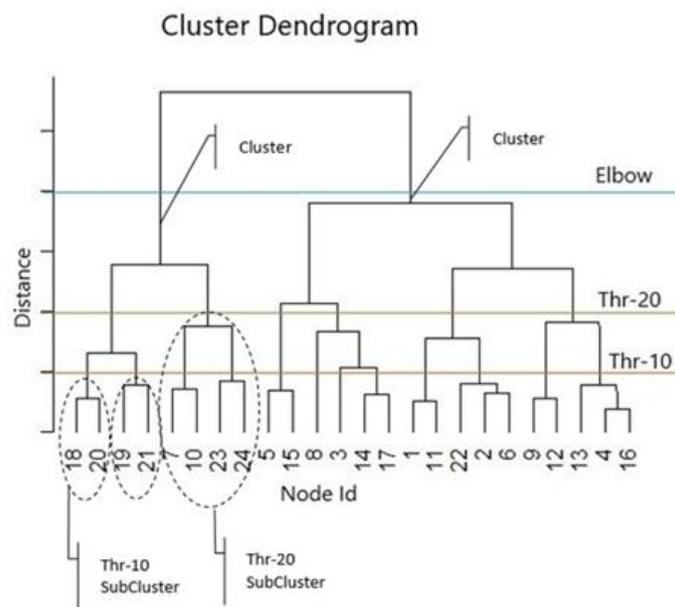

Figure 3. Hierarchical cluster dendrogram.

Table 1. Roles In Clustering And Subclustering

Node Type	Function
Normalnode	Collects and transmits data to the cluster head.
Cluster Head	Manages the cluster, aggregates data, and communicates with the base station.
Subhead	Manages a subcluster, aggregates data from Subnodes, and forwards it to the cluster head.
Subnode	Collects and transmits data to the Subhead, reducing communication overhead on cluster head.

5. EXPERIMENT AND ANALYSIS

To assess the effectiveness of the proposed clustering and subclustering algorithms in improving energy efficiency within the IoT sensor network, we will conduct a comprehensive performance assessment through simulation. We define relevant metrics, measure energy consumption and analyze scalability.

Energy efficiency is a critical aspect of ISNs, and various metrics are considered to measure its improvement. At the node level, energy consumption is measured by considering factors such as transmission power, reception power, and aggregation power. These metrics provide insights into the energy utilization patterns of the sensor nodes within the network. By comparing the energy consumption before and after implementing the clustering and subclustering algorithms, we can measure the improvements achieved in energy efficiency.

Simulation time is a performance metric that reflects the total duration required for the network to complete a simulation run. It provides insights into the computational and communication efficiency of different clustering and subclustering approaches. The impact of clustering and subclustering on overall network performance can be assessed by comparing the simulation times of various algorithms. Shorter simulation times indicate improved efficiency in processing and communication, while longer times may present higher computational overhead or increased message exchanges.

The proposed clustering and subclustering algorithms are implemented within the simulation, and the appropriate metrics are measured. Data collected during the evaluation phase is analyzed to evaluate the improvements in energy efficiency.

5.1 Experimental Setup

We are evaluating the performance of the proposed hierarchical clustering algorithm for ISNs using OMNeT++ as the simulation tool [28]. Parameters such as network size, and sensing range are adjusted to match the experiment's specifications. For instance, the network includes 100 sensor nodes, with the sensing range varied between 10 and 20 meters to simulate real-world scenarios [29, 30].

To emulate communication behavior within the ISN, we use appropriate communication models. We adopt a communication model similar to the one described in [31]. By using equations to calculate power consumption and transmission for n-bit data over a distance d, we determine the energy requirements for each sensor node. In these equations, E_{Tx} represents the power used for transmitting circuits, while E_{Rx} denotes the power consumption for receiving circuits. Additionally, E_{DA} represents the power necessary for data gathering. Each sensor node has a primary power supply of 0.9 joules. The parameter E_{elec} represents the energy consumed by electronic circuits, while ε_{fs} denotes the energy loss due to free-space propagation.

$$E_{Tx}(n, d) = n * E_{elec} + n * \varepsilon_{fs} * d^2 \tag{2}$$
$$E_{Rx}(n) = nE_{elec} \tag{3}$$
$$E_{DA} = 5nJ/bit/signal \tag{4}$$

We conducted all experiments using the OMNeT++ simulator with the parameters listed in Table 2.

Table 2. Simulation Parameters.

Parameter	Value
Size of sensing field	100m X 100m
Number of sensor nodes	50 ~ 100 nodes
Initial energy of each node	0.9 Joule
Base station location	50×175
E_{elec}	50 nJ/bit
ε_{fs}	10pJ $/bit/m^2$
Size of a data packet	500 bytes
Size of info packet	25 bytes

5.2 Performance Analysis

The experiments targeted energy efficiency and scalability improvement. Using a predefined methodology, we collected and analyzed performance data. We compared three algorithms: Thr-10 (hierarchical clustering with a 10-meter subclustering threshold), Thr-20 (with a 20-meter threshold), and HClstr (baseline hierarchical clustering without subclustering).

Figures 4 and 5 show the network lifetime of sensor nodes. The Thr-20 algorithm performed best on the First-Dead metric, with 226 rounds, and both Thr-10 and Thr-20 delayed energy depletion compared to HClstr. For the Half-Dead metric, Thr-10 and Thr-20 achieved 231 and 233 rounds respectively, while HClstr had 229 rounds. In the All-Dead metric, Thr-10 had the lowest value of 234 rounds, followed by HClstr with 236 rounds, and Thr-20 with the highest value of 244 rounds. These results indicate that the Thr-20 algorithm offers higher energy efficiency, resulting in an extended

network lifetime and delaying energy depletion compared to Thr-10 and HClstr.
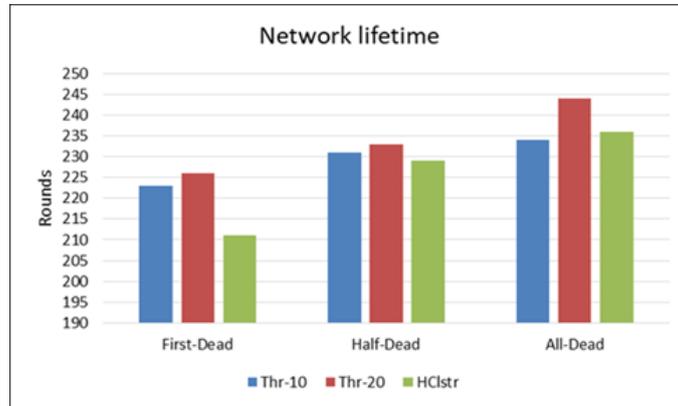

Figure 4. Network lifetime

The network lifetimes for the algorithms are as follows: Thr-10 ranges from 223 to 234 rounds, with an average of approximately 229.95 rounds. Thr-20 ranges from 225 to 244 rounds, averaging about 234.08 rounds. HClstr ranges from 211 to 236 rounds, with an average of approximately 228.9 rounds. These results show that HClstr achieves a reasonably prolonged network lifetime, with an average of 228.9 rounds, while Thr-10 averages slightly higher at 229.95 rounds. Thr-20 outperforms both, with the most extended network lifetime, averaging about 234.08 rounds.
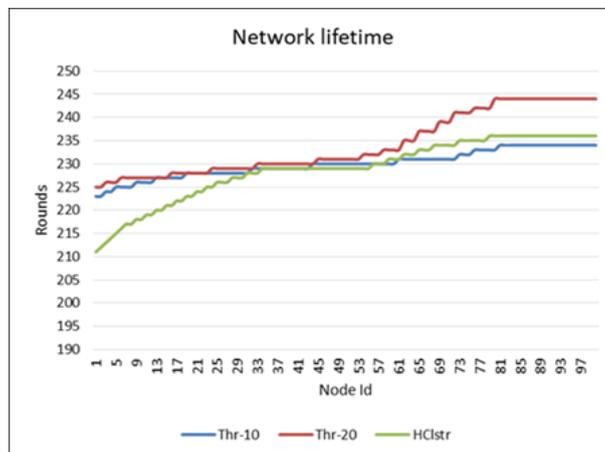

Figure 5. Network lifetime (Nodes)

The simulation time, measured in seconds, denotes the duration of each algorithm's simulation. Figure 6 details these findings:
- Thr-10 requires 44,520 seconds.
- Thr-20 completes in 25,142 seconds, faster than Thr-10.
- HClstr takes the longest at 98,467 seconds, exceeding both Thr-10 and Thr-20.

These results indicate that Thr-10 has a longer simulation time due to increased computational and communication overhead associated with a 10-meter subclustering threshold. In contrast, Thr-20 demonstrates a more efficient execution with a 20-meter threshold, reducing processing complexity and improving overall runtime.
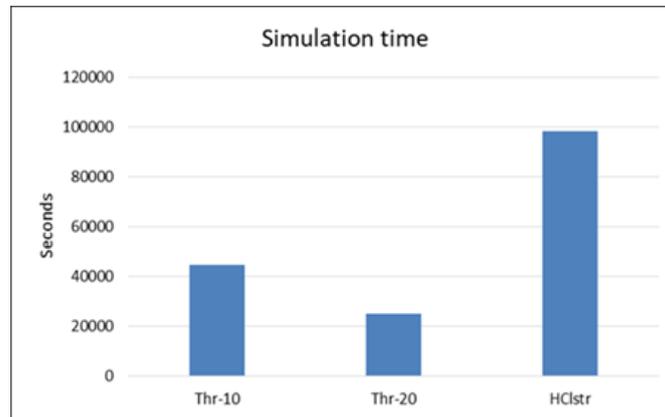

Figure 6. Simulation time.

On the other hand, HClstr exhibits the highest simulation time due to the absence of subclustering, leading to increased communication overhead and coordination among sensor nodes and cluster heads. Without subclusters, more messages are exchanged, and higher processing demands extend the total simulation runtime.

In summary, Thr-20 achieves the shortest simulation time, benefiting from an optimal balance between clustering and subclustering, which minimizes overhead and enhances computational efficiency compared to Thr-10 and HClstr.
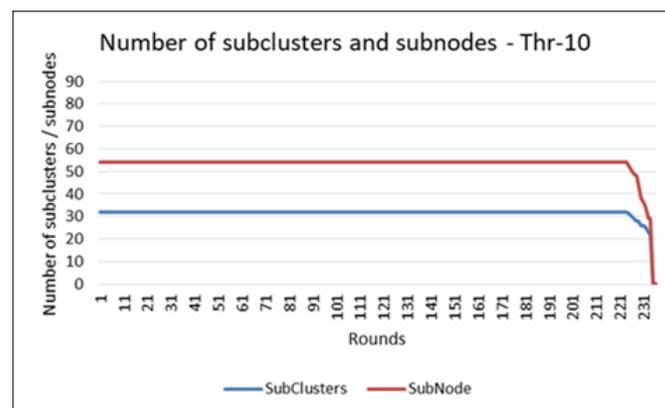

Figure 7. Number of subclusters and subnodes (Thr-10)

We have gathered data on the subclustering behavior of the Thr-10 and Thr-20 algorithms, as shown in Figures 7, 8, and 9. The Thr-10 algorithm maintains 32 subclusters consistently throughout the simulation, with each subcluster containing an average of 53 nodes. Similarly, the Thr-20 algorithm maintains 23 subclusters, each with an average of 75 nodes.

Both algorithms show stability in the number of subclusters and nodes, indicating strong scalability in subclustering. The approach of Thr-10 with 32 subclusters and Thr-20 with 23 indicates effective network partitioning with a balanced node distribution. However, the strategy of Thr-20 with fewer subclusters and more nodes per subcluster may be advantageous for larger, denser networks by ensuring a more uniform workload distribution.
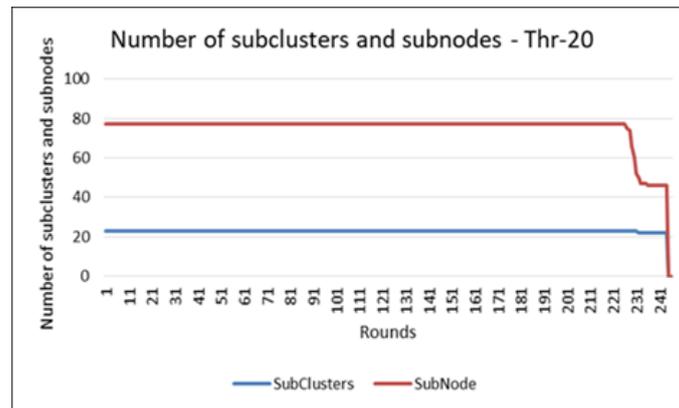

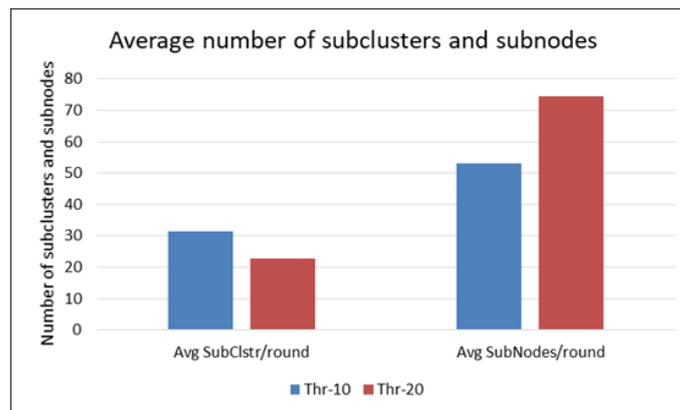**Figure 8.** Number of subclusters and subnodes (Thr-20)

Figure 9. Average number of subclusters and subnodes

Choosing between Thr-10 and Thr-20 depends on application-specific needs and other performance metrics such as energy efficiency, and network scalability.

6. CONCLUSION

In this paper, we have explored the application of hierarchical clustering algorithms, focusing on complete-linkage clustering, to enhance the performance of IoT Sensor Networks. Our methodology includes network division, cluster structure, and subclustering with dendrograms.

We initiated the network division using the complete-linkage hierarchical clustering algorithm, determining the optimal number of clusters using the elbow method. This approach allowed us to create clusters efficiently while considering critical factors such as network size,

communication range, and energy constraints. The cluster contains cluster heads and sensor nodes. Cluster heads were assigned based on criteria such as residual energy, ensuring a balanced distribution of energy consumption. Time-Division Multiple Access (TDMA) was used for efficient communication among nodes within clusters. Utilizing dendrograms, we established appropriate thresholds for subclustering within each cluster. These thresholds were aligned with the sensing range of sensor nodes. Each subcluster was guaranteed to contain at least two Subnodes, one of which served as the Subhead responsible for data aggregation before transmission to the cluster head.

Through experiments conducted in OMNeT++, we measured energy consumption at the node level. Also, scalability parameters assessed, including network size, the number of clusters, and the number of subclusters.

Our research benefits of hierarchical clustering, particularly the complete-linkage method, in optimizing ISNs. However, there are several opportunities for future improvement. Investigate adaptive methods for adjusting clustering parameters dynamically based on the network's real-time conditions. This could include dynamic clustering head selection or adaptive threshold determination for subclustering. Include a direct performance comparison of the proposed method with well-known clustering protocols such as LEACH and HEED. This comparative analysis will validate the performance improvements and contribute to a deeper understanding of the method's suitability for diverse ISN deployment scenarios.

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