IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

# Energy- Efficient Sleep Scheduling for QOS Cluster Head Nomination Enhancement In Wireless Sensing System

[1]Anoop.M, [2]William Mary. L,

[1]Assistant Professor, [2]Assistant Professor,

[1]Department of Computer Science and Applications,

[1]SRM Institute of Science and Technology, Ramapuram, Chennai, India

***Abstract:*** Wireless communication is made up of numerous constrained sensor node with constrained resources such as Energy capacity, Data transmission capacity, Battery longevity, Storage capability, Computational capacity. Sensor nodes generate massive volumes of data, which are subsequently gathered and transmitted to the sink through single or multi-bounds paths. Due to inadequate data transfer across nodes and excessive energy consumption caused by rising data transmission delay, the network becomes unstable due to the limited skills of the nodes. Network performance can be significantly impacted by sink locations and the paths that sensors take to get there. Although several solutions have been put out to deal with this problem, they frequently lead to networks that have limited lifespans, consume a lot of energy, and transport data slowly. Clustering is a helpful method for overcoming these constraints that can help wireless sensor networks operate better by consuming less energy. With the goal of increasing the lifespan of wireless sensor networks, this study applies a clustering technique to predict the optimization of two or more sink deployment and sensor-to-sink communication. We aggregate nodes using an improved mean shift approach initially, and then choose the cluster head using a QOS-aware cluster head selection. The suggested approach uses sleep scheduling and cluster-based routing for data transmission, which aids in quick routing and energy conservation.

***Keywords: wireless sensor networks; sink; mean shift algorithm; [QoS] Quality of Service; sensor-to-sink routing; data transmission; cluster based routing, sleep scheduling.***

## I. INTRODUCTION:

In recent decades, there has been a notable surge in the popularity of wireless sensor networks (WSNs). The ever-growing list of their uses in a variety of industries, including transportation, human activities in health care, industry, and battlefield, military surveillance, early detection of wildfires, monitoring of air pollution, and water monitoring demonstrate their success and the growing demand for them. A standard configuration for a wireless sensor network (WSN) comprises multiple sensor nodes (SNs) and a minimum of a single central hub station, often referred to as the sink. These sensor nodes, which are typically compact and constrained in terms of energy, processing capability, and memory, are strategically placed within the environment. They are responsible for sensing and gathering essential data, subsequently transmitting it either directly in a single bound or through various multi leap protocols to the nearest sink station, as described in reference [1].

Communication consumes over 70% of the battery power across different nodes within the network. In a sparse architecture wireless sensor network with constrained node capacities, the network's proper functioning is compromised when one of its sensors exhausts its power supply, as referenced in [2].In dense topology, the overlapped sensing zones greatly lengthen the network lifetime and increase wasteful energy consumption. To maximise the network's lifetime, it is vital to build an energy-efficient WSN. The lifetime is the amount of time before the first sensor node runs out of energy [3], and it can be increased by dramatically increasing the flow balance between nodes.

Energy usage during data transmission is inversely proportional to distance for SNs closer to the access points, and SNs closer to the central hub conserve a significant amount of energy for prolonged periods of time.Therefore, the amount of energy required for data transmission depends on the distance between communication nodes.The nodes closest to the sink in particular use less energy.The energy of the SNs nearest to the hub station is depleted as a result. In contrast, distant nodes might use other nodes to relay the data to the sink.In fact, the distance between the sink location and a sizable number of sensor nodes affects the network lifetime. Deploying multiple sinks as opposed to just one is a great strategy to construct an energy-efficient WSN [4].

The energy conservation modedrastically lowers energy consumption by awaking or putting to sleep sensors.The data aggregation algorithm is primarily used to process enormous data that, in its current inconsistent state, does not provide its owner with useful information. The compressed sensing method reduces the amount of transmitted measurements and, as a result, achieves an appealing reduction in network energy consumption by making use of the redundancy contained in environmental WSN data.However, it requires extensive data preparation, which is contrary to the processing and energy constraints of the Ambient Intelligence domains.

Broadly speaking, sensor nodes can be deployed in diverse settings using a range of technologies. For instance, Wireless Body Sensor Networks (as cited in [5]) involve the implantation of various biomedical sensors (such as those measuring body temperature, blood pressure, heartbeat, etc.) within the human body over an extended duration. This approach contributes to cost reduction in healthcare by enabling the collection and analysis of patient vital-sign-related data. Additionally, the Vehicular Ad-hoc Network (VANET), an integral part of the Intelligent Transport System (ITS) (as mentioned in [6]), facilitates wireless communication among moving vehicles, enhancing transportation systems. This unique Mobile Ad-hoc Network (MANET) has a specific structure. Numerous Unmanned Aerial Vehicle (UAV) nodes form the Flying Adhoc Network (FANET) [7] by way of wireless connections. Remote control or pre-programmed instructions can be used to operate UAVs.

In this study, we offer an effective model based on clustering that predicts the appropriate position of cluster heads for multiple sinks and routing data paths in WSNs. This model is inspired by enhanced ant clustering algorithm methods. Some important findings from our research that relate to the suggested model-based clustering include the following:

1. We offer a comprehensive model with the goal of extending the network's lifetime. The strain on the sensor nodes is reduced since it completes crucial activities including sink placement, path creation from sink to CH, and CH selection.

2. When our approach is in operation, no intermediate node participates or transmits their data packets with less dynamism than a threshold and greater distance than a threshold, which results in large power savings.

3. In order to find areas of limitation, we evaluated our suggested technique with others in a variety of simulation conditions and discovered that it outperformed all of them. We noted that the residual energy increased by more than 2.8% although the number of bounds was reduced by more than 4% to one leap.

## II. RELATED WORKS

Data routing, sink assignment, and ideal multiple sink placements are just a few of the variables that can affect how much power is used and how long a network can last.

### 2.1. SINK POSITION

In scenarios requiring extensive deployment, such as environmental monitoring, industrial networks, surveillance, and agricultural settings, single-sink solutions prove to be less efficient. A preliminary investigation conducted by [8] employed an iterative clustering technique, incorporating multiple sinks, to determine the optimal placement for each sink, with the primary goal of prolonging the network's lifespan.They divided the entire network into clusters using the K-means approach in order to assure the network's scalability, with each sink being located in the power-efficient middle of each cluster. Sinks are added until the required lifespan is obtained. Nevertheless, this technique proves unsuitable for numerous applications due to the substantial number of sensor nodes (SNs) and the fixed, deterministic placement of sinks at static locations within the network. In contrast, another research endeavor [9] employed mixed integer linear programming (MILP) to optimize the positioning of sinks and the associated sensor-to-sink communication, aiming to enhance the network's longevity and streamline the routing of the PSO algorithm toward the sink. While this model effectively extended the network's lifespan, it may have resulted in a less direct route. Alternatively, an analytical approach proposed in [10], which involves distributing k-sinks within the network based on the k-median problem, offers a potential solution to address the strength hole issue and ultimately extend the network's lifespan. Since the sinks in cognitive WSN are not equipped to process the data from every sensor, the model did not specify the types of applications employed. In other investigations [11], scheduling, routing, sink location, and sensor position were all combined.

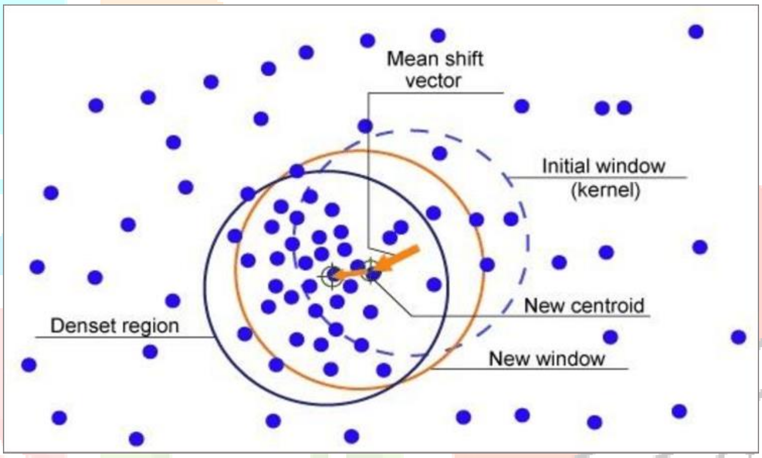


Figure 1.Mean shift clustering procedure

### 2.2. DATA ROUTING AND TRANSMISSION PATHS

Each sensor's key job in a WSN is to send its observed data to the sink on a regular basis. Direct Transmission (DT) [12] is a straightforward technique that eliminates the need for an intermediary node by allowing sensors to broadcast directly to sink nodes. This arrangement is typically used in networks with topologies where a central node is responsible for managing operations. But it leads to an uneven loss of power throughout the nodes. Nodes put far from the sink deplete more quickly as a result than nodes placed close to the sink.

Hierarchical routing employs clustering techniques as a strategy to enhance network performance. In this approach, nodes are organized into clusters, each led by its own designated head node. These Cluster Head nodes play a crucial role in collecting and consolidating data within their respective clusters, and subsequently, they relay this aggregated data to the sink node. Some widely recognized hierarchical routing systems include "Low dynamism Adaptive Clustering Hierarchy" [13], "Power-Efficient Gathering in Sensor Information Systems" [14], "Centralized zeal-Efficient Distance" [15], "Threshold-Sensitive power-Efficient Sensor Network Protocol" [16], and "General Self-Organized Tree-Based Energy-Balance" [17].

The distance between nodes and the appropriate sink is critical in choosing the best method to convey the ac quired data in an energy-efficient routing strategy [18].In actuality, this low-energy routing strategy should lower communication costs.In ref. [19], which combined CDG with clusterin g, blockdiagonal matrices were utilised as measurement matrices.The use of transmission power has lowere d dramatically as a result of WSNs. But these cluster-based CDG techniques still necessitate a sizable number of intra-cluster data exchanges. Additionally, no prior studies have examined the robustness of Signal recovery performance in the event of a network node failure.

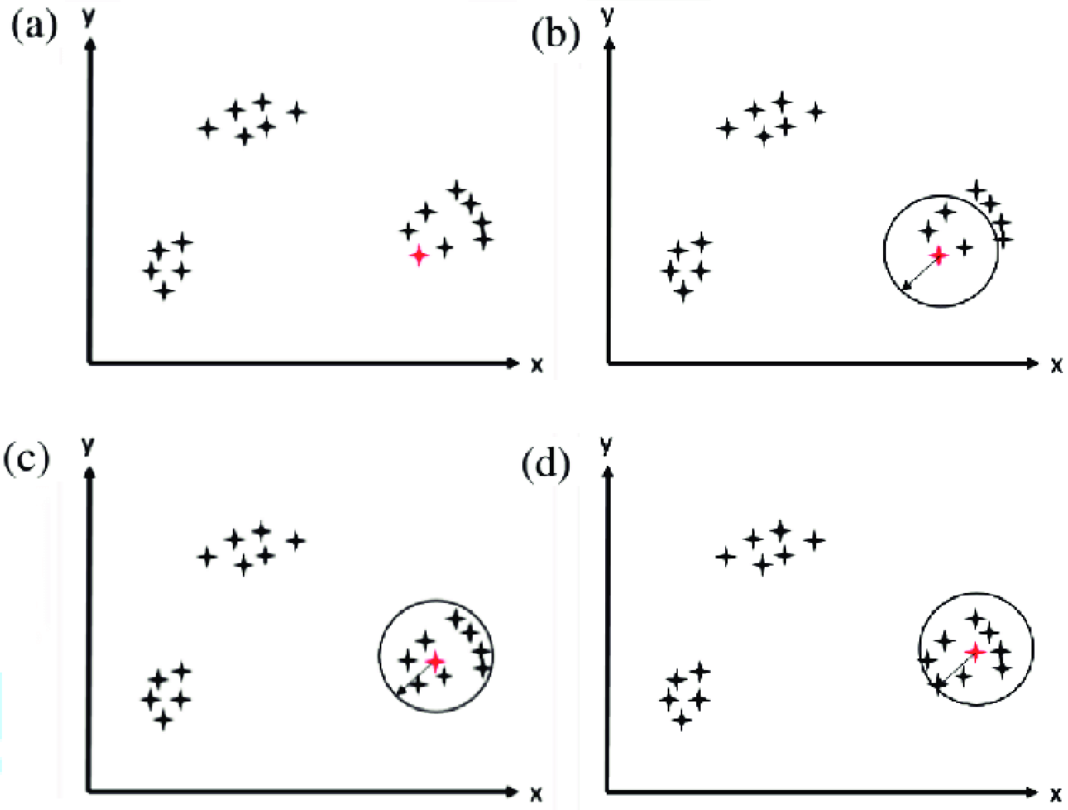


Figure 2. Diagram fixing cluster heads

## III. PROBLEM DEFINITION

The central challenge in wireless sensor networks (WSNs) lies in the efficient organization and management of sensor nodes. One fundamental aspect is data clustering, wherein a dataset of sensor nodes must be grouped into clusters based on data similarity or dissimilarity metrics. The primary objective is to create clusters where nodes within the same cluster exhibit similarity while maintaining dissimilarity between clusters. This clustering process is essential for various WSN applications, including data aggregation, anomaly detection, and resource optimization. Achieving effective clustering entails addressing issues such as energy efficiency, decentralized operation, dynamic adaptation, and scalability, as these characteristics are vital for the long-term functionality and performance of WSNs.

Within the context of WSNs, cluster head (CH) selection is a critical component of efficient data management. CHs serve as intermediaries between sensor nodes and the network's central sink or gateway. The challenge is to select CHs judiciously to optimize energy consumption and evenly distribute the energy-intensive CH role throughout the network. This involves minimizing energy expenditure while ensuring reliable data transmission and aggregation. CH selection methods should also be dynamic, adapting to changing network conditions and node failures, and should consider metrics such as network lifetime, communication overhead, and quality of service.

The overarching problem encompasses both data clustering and CH selection in WSNs, aiming to strike a balance between energy efficiency and data management quality. Key considerations include designing distributed algorithms that operate autonomously on local information, accommodating network scalability, and addressing security and fault tolerance as needed. Additionally, relevant quality metrics, such as intra-cluster and inter-cluster distance, network lifetime, communication overhead, and data aggregation efficiency, are used to evaluate the effectiveness of solutions developed for this problem domain. Ultimately, solving this problem contributes to the sustainable and reliable operation of WSNs, supporting applications ranging from environmental monitoring to industrial automation and healthcare systems.

### 3.1.MEAN SHIFT CLUSTERING

This is a powerful non-parametric technique used for clustering data points based on their density or similarity. It doesn't require prior knowledge of the number of clusters, making it versatile for various applications. At the core of this algorithm are two essential formulas: the kernel function (P) and the mean shift vector (M).

The kernel function (P) quantifies the similarity between data points. A commonly used kernel is the Gaussian kernel, which assigns higher values to points that are closer to each other in the feature space. The bandwidth parameter controls the width of this kernel, determining the influence radius of each data point. A smaller bandwidth results in a tighter kernel and smaller clusters, while a larger bandwidth leads to broader kernels and larger, more diffuse clusters.

$$P(x, x\_i) = exp(-||x - x\_i||^2 / (2 * bandwidth^2)) \quad (1)$$

Here, x is the point of interest, x_i is a data point, and bandwidth is a parameter that controls the kernel's width.

The mean shift vector (M) guides the iterative process of cluster formation. It calculates the direction and magnitude of the shift for each data point towards the mode or peak of the data distribution. By iteratively applying this shift to all data points, clusters start to form around local density maxima. Data points within a certain distance of each other, determined by the bandwidth, are grouped into the same cluster. This process continues until convergence, resulting in clusters that capture the underlying data distribution's modes or peaks.

In practical terms, the Mean Shift algorithm initializes cluster centers as data points and then shifts them iteratively towards the highest density regions, attracting nearby points until convergence. Those points within the bandwidth distance of each shifted center form a cluster. This process repeats until no more significant shifts occur, leading to a clustering solution that adapts to the data's density distribution. It's particularly valuable when the number of clusters is not known in advance and can discover complex cluster shapes in the data.

$$M(x) = \Sigma [P(x, x\_i) * x\_i] / \Sigma P(x, x\_i) \quad (2)$$

This formula calculates the mean shift for point x.

### 3.2.QUALITY OF SERVICE (QOS)- CLUSTER HEAD NOMINATION ENHANCEMENT

The above head nomination in wireless sensor networks (WSNs) is crucial for optimizing network performance, particularly in energy-constrained environments. One of the key QoS metrics often considered in WSNs is energy efficiency, which plays a vital role in prolonging network lifetime. The provided formula for energy efficiency metric (EEM) encapsulates this concept by taking into account both a node's residual energy and its energy consumption for data transmission and reception.

In the context of Mean Shift clustering, once clusters have been formed, the selection of cluster heads based on energy efficiency becomes paramount. The formula outlined ensures that the most energy-efficient node within each cluster is chosen as the cluster head. By selecting cluster heads with the highest EEM values, the network can benefit from nodes that are more likely to operate efficiently and consume less energy during their role as cluster heads.

$$EEM(i) = f(r(i), e(i)) \quad (3)$$

r(i): Residual node energy i (measured in joules or other energy units).

e(i): Node I uses energy to send and receive data. (measured in joules).

f(r, e): A function that combines residual energy and energy consumption to quantify energy efficiency. This function can vary depending on the application and network requirements.

This approach to QoS-aware cluster head selection is vital for maintaining network longevity, especially in scenarios where replacing or recharging sensor node batteries may be impractical. By prioritizing energy-efficient nodes as cluster heads, the network can make more efficient use of its available resources, reduce energy wastage, and improve overall network performance while adhering to energy constraints. The flexibility of this approach allows it to be adapted to various QoS metrics and specific application requirements in WSNs, ensuring that the network operates optimally according to its intended goals.

Formula for Cluster Head Selection:

$$Cluster\_Head(i) = argmax(EEM(j))\ for\ all\ nodes\ j\ in\ cluster\ C\_i \qquad (4)$$

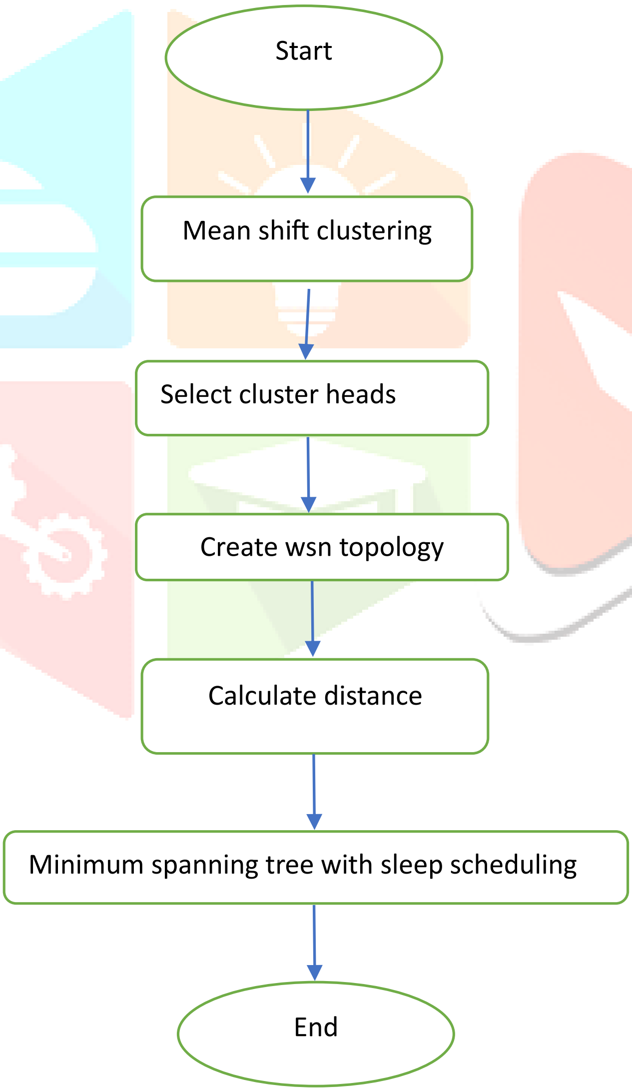


Figure 3. Flowchart of working model

```
qos_requirements = {
    "latency": threshold_latency,
    "reliability": threshold_reliability,
    "energy_efficiency": threshold_energy
}
clusters = mean_shift_clustering(data_points, bandwidth_parameter)
selected_cluster_heads = {}
for cluster_id, cluster_data in clusters.items():
    best_candidate = None
    best_candidate_score = -infinity
    for node in cluster_data:
        qos_score = calculate_qos_score(node, qos_requirements)
        if qos_score > best_candidate_score:
            best_candidate = node
            best_candidate_score = qos_score
    selected_cluster_heads[cluster_id] = best_candidate
Function CreateWSNTopology(numNodes, radius):
    WSNGraph <- CreateGraph(numNodes)
    For each node in WSNGraph:
        Randomly position node in the WSN area
    For each pair of nodes (node1, node2) in WSNGraph:
        If distance(node1, node2) <= radius:
            Add an edge between node1 and node2 with weight = distance(node1, node2)
    Return WSNGraph
Function CalculateDistance(node1, node2):
        Return EuclideanDistance(node1.position, node2.position)
Function MSTWithSleepScheduling(WSNGraph, slotDuration):
        MSTGraph <- MinimumSpanningTree(WSNGraph)
    numNodes <- Number of nodes in MSTGraph
    timeSlots <- GenerateTimeSlots(numNodes)
    sleepSchedule <- Dictionary()
    activeSlots <- List()
    For each node in MSTGraph:
        Randomly shuffle timeSlots
```

*sleepSchedule[node] <- timeSlots.Copy()*

*activeSlots.Add(slotDuration)*

*Return MSTGraph, sleepSchedule, activeSlots*

**Algorithm. 1 Mean Shift-QOS Aware cluster head with sleep scheduling.**

The provided code snippet and accompanying functions outline a sophisticated network management scheme that seamlessly integrates several critical components. It commences by defining the network's Quality of Service (QoS) requirements through the qos_requirements dictionary, which sets thresholds for latency, reliability, and energy efficiency, serving as the benchmark for subsequent operations.

Following this, the Mean Shift Clustering algorithm is applied to a dataset (data_points) with a specified bandwidth_parameter, resulting in the creation of clusters (clusters). These clusters group similar data points, enhancing the organization of sensor nodes within the network.

The cluster head selection process is a pivotal part of this network management approach. The code iterates through each cluster and evaluates nodes based on their ability to meet the QoS requirements. It initializes variables to track the best cluster head candidate and their associated QoS score. This rigorous selection process ensures that the cluster head chosen for each cluster is optimally suited to meet the network's QoS demands. The selected cluster heads are stored in the selected_cluster_heads dictionary for future reference.

Additionally, the code includes functions for creating a random Wireless Sensor Network (WSN) topology and performing Minimum Spanning Tree (MST) construction with sleep scheduling. The WSN topology is generated with numNodes nodes, randomly positioned within a specified communication radius. The MST construction ensures efficient data routing and energy conservation. Sleep schedules and active slot durations are strategically assigned to nodes within the MST to optimize energy consumption, contributing to the network's longevity and performance.

### 3.3.SLEEP SCHEDULING:

Sleep scheduling determines when nodes should transition between active and sleep states. One common approach is to use TDMA (Time-Division Multiple Access) scheduling, where each node operates on a predetermined time slot. The formula to calculate the duration of active and sleep slots can be expressed as:

$$\text{Active Slot Duration} = (\text{Percentage of time nodes remain active}) * (\text{Total Slot Duration}) \quad (5)$$

$$\text{Sleep Slot Duration} = \text{Total Slot Duration} - \text{Active Slot Duration} \quad (6)$$

### 3.4.DATA ROUTING:

Data from sensor nodes is routed to the cluster head during their active slots. Cluster heads aggregate and forward data to the sink. Data routing can be optimized using various algorithms, such as Minimum Spanning Tree (MST) for energy-efficient tree-based routing. The formula for computing the MST is based on the network's connectivity and can be derived from graph theory.

### 3.5.NS-3 (NETWORK SIMULATOR 3)

This is a widely used discrete-event network simulator that is primarily designed for general-purpose network simulations. While NS-3 is not specifically tailored for Wireless Sensor Network (WSN) simulations out of the box, it is highly extensible and flexible, allowing researchers and developers to extend its capabilities to simulate WSNs and other specialized network scenarios.

Here's an explanation of how NS-3 can be extended for WSN simulations:

NS-3's modular and extensible architecture empowers researchers and developers to tailor their network simulations for Wireless Sensor Networks (WSNs) with precision and flexibility. By crafting custom modules and components, users can emulate sensor nodes, energy models, and communication protocols that mirror real-world WSN behavior. This customization extends to modeling the intricacies of sensor nodes, including energy consumption patterns, data transmission, and sensing capabilities. Moreover, NS-3 accommodates bespoke communication protocols designed specifically for WSNs, allowing researchers to simulate node communication, clustering, and data routing. These simulations can account for strict energy constraints, accurately modeling node energy consumption. NS-3 further aids analysis through its visualization tools, enabling the creation of tailored visualization modules to present WSN-specific data effectively. The thriving NS-3 user community has contributed a wealth of WSN-related modules and extensions, easing the process of launching WSN simulations and fostering collaborative advancements in the field.

## IV. FUTURE ENHANCEMENT

The combination of the Mean Shift clustering algorithm with a QoS-aware cluster head selection algorithm should focus on improving scalability, adaptability to dynamic network conditions, and incorporating machine learning for predictive QoS management. Additionally, exploring multi-objective optimization, distributed or decentralized approaches, security measures, cross-domain applicability, and standardized performance metrics will enhance its versatility. Incorporating user-friendly interfaces, energy-efficient strategies, open-source implementations, and benchmark datasets will promote usability, collaboration, and robust evaluations, ensuring the algorithm's effectiveness in diverse networked systems and data analysis contexts.

## V. CONCLUSION

The combination of the Mean Shift clustering algorithm with a QoS-aware cluster head selection algorithm offers promising prospects for improving cluster formation, data quality, resource allocation, and QoS parameters in networked systems. This hybrid approach leverages Mean Shift's ability to discover dense data regions, facilitating more coherent clusters, while QoS-aware selection ensures that cluster heads possess the necessary capabilities to meet quality requirements. However, its scalability, adaptability to varying data conditions, and practicality in real-world applications should be thoroughly assessed, and parameter tuning may be necessary for optimal performance, making it a subject of further investigation for specific use cases.

## REFERENCE

**[1]** Bouarourou, S.; Zannou, A.; Boulaalam, A.; Nfaoui, E.H. December 2022; Sensors Deployment in IoT Environment. In Proceedings of theInternational Conference on Digital Technologies and Applications, Fez, Morocco, 15–20 pp. 276–283.1.

**[2]** Zannou, A.; Boulaalam, A.; Nfaoui, E.H. 2020,SIoT: A New Strategy to Improve the Network Lifetime with an Efficient Search Process.Future Internet, 13, 4

**[3]** Mishra, S.; Thakkar, H., 2012, Features of WSN and Data Aggregation techniques in WSN: A Survey. Int. J. Eng. Innov. Technol.(IJEIT), 1, 264–273.

**[4]** Oyman, E.; Ersoy, C. 2004, Multiple sink network design problem in large scale wireless sensor networks. In Proceedings of the 2004 IEEE International Conference on Communications (IEEE Cat. No.04CH37577), Paris, France, 20–24 ; pp. 3663–3667.

**[5]** Bangash, J.I.; Abdullah, A.H.; Anisi, M.H.; Khan, A.W. 2014, A Survey of Routing Protocols in Wireless Body Sensor Networks. Sensors, 14, 1322–1357

**[6]** Malik, A.; Khan, M.Z.; Faisal, M.; Khan, F.; Seo, J.-T.2022, An Efficient Dynamic Solution for the Detection and Prevention of Black Hole Attack in VANETs. Sensors, 22, 1897.

**[7]** Lansky, J.; Ali, S.; Rahmani, A.M.; Yousefpoor, M.S.; Yousefpoor, E.; Khan, F.; Hosseinzadeh, M. 2022, Reinforcement Learning-Based Routing Protocols in Flying Ad Hoc Networks (FANET): A Review. Mathematics , 10, 3017.

**[8]** Oyman, E.; Ersoy, C. 2004, Multiple sink network design problem in large scale wireless sensor networks. In Proceedings IEEE International Conference on Communications (IEEE Cat. No.04CH37577), Paris, France, pp. 3663–3667.

**[9]** Zhao, C.; Wu, C.; Wang, X.; Ling, B.W.-K.; Teo, K.L.; Lee, J.-M.; Jung, K.-H.2017, Maximizing lifetime of a wireless sensor network via joint optimizing sink placement and sensor-to-sink routing. Appl. Math. Model.,49, 319–337.

**[10]** Tsoumanis, G.; Oikonomou, K.; Koufoudakis, G.; Aïssa, S.2018, Energy-efficient sink placement in wireless sensor networks. Comput.Netw. , 141, 166–178

**[11]** Kabakulak, B.2019, Sensor and sink placement, scheduling and routing algorithms for connected coverage of wireless sensor networks Ad Hoc Netw., 86, 83–102

**[12]** Heinzelman, W.R.; Chandrakasan, A.; Balakrishnan, H. 2000,Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, Maui, Hawaii,;Volume 2, p. 10.

**[13]** Handy, M.; Haase, M.; Timmermann, D. 2003,Low energy adaptive clustering hierarchy with deterministic cluster-head selection. In Proceedings of the 4th International Workshop on Mobile and Wireless Communications Network, Lake Buena Vista, FL, USA,

**[14]** Lindsey, S.; Raghavendra, C. 2002 , PEGASIS: Power-efficient gathering in sensor information systems. In Proceedings of the Aerospace Conference Proceedings, Big Sky, MT, USA,; Volume 3, pp. 1125–1130.

**[15]** Gawade, R.D.; Nalbalwar, S.L. 2016,A Centralized Energy Efficient Distance Based Routing Protocol for Wireless Sensor Networks.J. Sens., 1–8.

**[16]** Manjeshwar, A.; Agrawal, D.P.2001, TEEN: ARouting Protocol for Enhanced Efficiency in Wireless Sensor Networks. ipdps, 1, 189.

**[17]** Han, Z.; Wu, J.; Zhang, J.; Liu, L.; Tian, K.2014, A general self-organized tree-based energy-balance routing protocol for wireless sensor network. IEEE Trans. Nucl. Sci. , 61, 732–740.

**[18]** Pantazis, N.A.; Nikolidakis, S.A.; Vergados, D.D.2012, Energy-Efficient Routing Protocols in Wireless Sensor Networks: A Survey.IEEE Commun. Surv. Tutor., 15, 551–591.

**[19]** Sun, P.; Wu, L.; Wang, Z.; Xiao, M.; Wang, Z. 2018,Sparsest Random Sampling for Cluster-Based Compressive Data Gathering in Wireless Sensor Networks. IEEE Access, 6, 36383–36394.