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Machine Learning based Data Sensing Device Network with Optimized Group Formation and Group Head Selection

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Abstract: - Sensor devices for data sensing (referred to as DSDs) are used in use cases such as border control and vehicle tracking. The architecture of the Data Sensing Device Network (DSDN) is established by integrating numerous DSDs across a given region, forming multiple groups. Within each group, a specific DSD is designated to facilitate communication between independent groups. The multi attribute values are captured and these attribute values effect the selection of head DSDs. For each of DSD this value ranges between 0.1 to 1. The DSD which has the highest value of range will be treated as Group Head in LEACH. The attributes are namely distance, battery level for each DSD. From the source DSD to destination DSD the link formation will happen end to end by making use of DSDs and base station, generally the end-to-end link communication has larger hops. This will have a ripple effect on battery level for DSDs and can cause reduced lifetime. The Energy based LEACH is modified on top of LEACH by computing the battery level for DSDs and picking DSD with highest battery level. The Energy based LEACH will have two DSDs in each group acting like head DSDs. Machine Learning Data Sensing Device Network (ML-DSDN) is proposed which will first create group DSDNs based on k means machine learning algorithm. ML-DSDN will find the head group DSD based on combination of random forest and SVM algorithm with set theory. The comparison is done of ML-DSDN with respect to ELEACH and LEACH method and it is proved that ML-DSDN performs better with respect to delay, link count, energy consumption, alive DSD count, dead DSD count, lifetime ratio, routing overhead.

Keywords: ELEACH, LEACH, Machine Learning Data Sensing Device Network (ML-DSDN), of Quality of Service (QoS).

I. INTRODUCTION

The study presents a novel Hybrid protocol tailored for Wireless Sensor Networks (DSDN), which builds upon the LEACH protocol through the integration of Machine Learning techniques. This protocol prioritizes factors such as traffic patterns, energy levels, and distances within the network to enhance its overall performance. Initially, the protocol employs the K-medoid algorithm for clustering, a method recognized for its effectiveness in forming clusters based on distances between data points. By considering various parameters including distance, traffic load, and energy levels, the protocol intelligently selects cluster head candidates. Furthermore, in the re-clustering phase based on machine learning technique the cluster head is elected, is utilized. A significant development has occurred in DSDN with the rise of the Internet of Things (IoT). The fundamental goal of IoT is to enable the transfer of data collected from DSDN networks to distant locations (referred to as sinks) using different wireless technologies, all while minimizing delays and conserving energy. The time required to collect and process data at the DSD level is critical in communication latency, a key measure of Quality of Service (QoS). Latency includes several processes such as data collection, processing, transmission across multiple hops, and ultimately reaching the sink DSD. Many protocols have been created to assess latency in DSDNs. Energy consumption is another important metric for DSDN QoS. Various energy-efficient routing protocols have been developed specifically for DSDNs. In DSDNs, each DSD is initially endowed with a certain amount of energy, which is expended during activities such as cluster creation, sensing, processing, data transmission, reception, and store-and-forward operations. The proposed work aims to optimize communication latency and energy consumption across the entire network. Communication within the network adheres to a network model where each layer plays a vital role and exchanges data with its adjacent layers. Collaborative operation between layers, known as cross-layer optimization, enhances overall performance.

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The suggested protocol utilizes a cross-layer approach where the Network, Media Access Control (MAC), and Physical layers work together to achieve energy efficiency, reduce the number of inactive nodes, minimize latency, and maximize the number of operational nodes. Extending the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol with additional functionalities, the proposed protocol integrates probabilistic, distance-based, and energy-aware criteria for selecting DSDN heads. Each chosen DSDN head takes on the responsibilities of sensing its own data, collecting data from other DSDN nodes, and transmitting processed data to the next DSD, all with the goal of accelerating data delivery to the sink while conserving energy. The protocol's intelligent cross-layer routing mechanism utilizes a sequence of DSDN heads to relay processed data to the remote sink. The process of selecting DSDN heads, gathering and processing data, and optimizing the transmission path involves collaborative efforts across the Network layer, MAC layer, and Physical layer, showcasing the comprehensive cross-layer functionality of the protocol. The paper is structured as follows: it begins with a survey of various existing methods, followed by a detailed explanation of the proposed method. This explanation covers DSDN formation, cluster formation, DSDN head selection, path establishment, data delivery process, and data aggregation.

II. BACKGROUND

Many contemporary applications involve the continuous flow of data, commonly referred to as data streams. One prominent domain reliant on data streams is the realm of DSDN applications. Given the limited lifespan of sensors, there exists a pressing need to devise algorithms for aggregating sensor data within the DSDN domain. Introducing W-LEACH, an innovative data-stream aggregation algorithm tailored for DSDNs, which builds upon the LEACH algorithm proposed by Heinzelman et al. W-LEACH exhibits versatility in handling both non-uniform and uniform networks without compromising network longevity. In fact, W-LEACH enhances the average sensor lifespan, ensuring sustained network performance. DSDNs have gattered lot of attention within the research community, catalysing a transformative shift in technology with immense potential to enhance numerous existing applications. DSDNs find relevance across diverse domains such as habitat monitoring, building surveillance, forest surveillance, and earthquake observation, among others. While these applications traditionally have focused on environmental monitoring, they now play pivotal roles in fields such as biological science, biomedical engineering, healthcare, and vehicle tracking. Sensors deployed in these applications are often dispersed remotely and operate autonomously. However, DSDNs encounter several constraints, including limited energy resources, processing capabilities, and communication range [2] – [5]. In DSDN network, DSDs are outfitted with small-scale devices designed to detect various phenomena in their surroundings. These DSDs possess the capability to sense, process, and transmit data or information. These devices have the capability to communicate with neighbouring DSDs and transmit information to the base station. This communication can occur either directly or through intermediate relay DSDs [6]. A significant obstacle in DSDN applications revolves around minimizing energy consumption and extending the network's lifespan. Efforts are directed towards reducing energy usage among end DSDs or sensor DSDs to prolong the overall network lifespan. This entails minimizing processing tasks and communication overhead associated with each sensor DSD within the DSDN [7].

LEACH (Low Energy Adaptive Clustering Hierarchy) functions as a hierarchical protocol designed for routing data within group-based DSDNs. It offers several benefits including self-organization and adaptability. LEACH operates in rounds, each comprising two stages: group setup and steady-state. During the steady-state phase, a group of DSDs operates with the objective of conserving energy and minimizing unnecessary energy consumption. However, it's worth noting that the steady-state phase is typically shorter in duration compared to the group setup phase [8]. Energy efficiency stands as a critical concern in DSDNs due to the finite battery power available to sensor DSDs. This study introduces a novel energy-efficient routing protocol, termed ML-EERP, which leverages machine learning techniques and incorporates traffic awareness. ML-EERP begins with initial clustering facilitated by the K-medoid algorithm and subsequently employs machine learning for cluster head selection, considering factors like distance, traffic load, and energy levels. The protocol's experimental assessment primarily examines the efficacy of selecting optimal cluster head candidates and their impact on energy efficiency. Through comparative analysis with the conventional LEACH protocol, the study evaluates

The performance of ML-EERP was evaluated based on network lifetime, throughput, packet delivery ratio, and energy consumption. Experimental results demonstrate substantial improvements in energy efficiency compared to LEACH, highlighting the effectiveness of using machine learning for selecting group heads and enhancing overall network performance[9]. Lizhi Cao and Ying Chen have proposed an energy-balanced unequal group algorithm designed specifically for DSDNs known as Detection Sensor Devices (DSDs), aiming to address the challenges posed by the random distribution of DSDs. Drawing inspiration from the ICLA protocol and integrating learning automata (LA), this algorithm takes into account DSD density to achieve energy balance throughout the DSDN. The proposed approach incorporates criteria such as residual energy and DSD density in the process of selecting group heads, leveraging learning automata for intelligent decision-making. By considering the distance between group heads and the base station, along with DSD density, the algorithm forms unequal groups to effectively distribute the energy load across the DSDN. Furthermore, it utilizes an evaluation function to identify optimal relay group heads and establish multi-hop routing, thus achieving a balance between group head energy, DSD density within groups, and distances to the base station. Through these strategies, the algorithm aims to optimize group head selection and ensure a balanced distribution of energy load among all DSDs within the DSDN [10].

Mobile Ad hoc Networks (MANETs) have become a significant technology in wireless communication, offering advantages such as mobility support, scalability, and DSDN extension without reliance on fixed infrastructure. However, wireless connectivity introduces several communication challenges, including connection lifespan, packet routing, information delay, and ensuring security and trustworthiness of data sources and receivers. The traditional flat topology used in MANETs encounters difficulties in scaling with the growing number of mobile devices. To address this, hierarchical topologies like groups have been proposed to tackle scalability issues. groups of mobile devices resolves key problems including DSDN expansion, confining communication within clusters to maintain neighbor group unawareness, and simplifying routing maintenance. groups involves two primary processes: group formation and group maintenance. The author discusses weighted groups, a scheme that imposes constraints on fixed weights (Degree Difference Nv, Sum of Distances Dv, Mobility Mv, and Power Pv). These weights are crucial for selecting stable group heads and supporting the dynamics of mobile devices. The algorithm focuses on selecting the mobile device with the minimum weight to serve as the group head, a critical task in both group formation and maintenance phases. [11]. DSDN is a system created to monitor its surroundings, process collected data, and enable communication among its sensor devices. These activities require energy, usually provided by batteries, to operate effectively in real-time. Many research efforts have investigated ways to improve power efficiency within DSDNs. This study aims to develop an adaptive framework that utilizes machine learning techniques within DSDNs. The research evaluates how integrating machine learning methods into DSDNs can impact energy efficiency [12]. The selection of group heads is critical for the longevity of a DSDN as it effectively manages energy consumption across DSDs. Previous studies have primarily emphasized factors such as residual energy levels and distances to the base station when addressing this issue. As per the study the lifespan of the DSDN depends on the time until the first DSD device depletes its energy reserves, making this criterion worthy of attention. This research introduces an enhanced energy-efficient protocol that utilizes K-means clustering, where both distance and residual energy are key parameters aimed at extending the lifespan of the initial DSD device until its energy reserves are depleted [13].

Laxminarayan Sahoo and Team proposed a method which first finds Group Heads (GHs) for group DSDN purposes. These intelligent clustering algorithms leverage data-driven approaches, machine learning, and optimization algorithms to facilitate optimal DSDN formation and Group Head selection. An intelligent clustering mechanism has been devised utilizing the Silhouette Index (SI) score, which serves as a benchmark for conducting optimized clustering using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. Additionally, we utilized the elbow method to corroborate the SI score in conjunction with the k-Means clustering algorithm. By incorporating uncertainty factors into the decision-making process algorithms demonstrate adaptability to changing conditions, thereby enhancing the overall lifetime of the DSDN. Furthermore, our framework integrates MCDM approaches to prioritize cluster formation and GH selection criteria. Triangular Fuzzy Numbers (TFNs) are utilized to represent uncertain parameters, as they align well with the principles of fuzzy logic systems designed to handle uncertainty and imprecision [14]. Distributed Sensor Device Networks (DSDNs) are often deployed in remote and inaccessible areas to facilitate precise environmental monitoring for various applications in civil and military sectors. These networks utilize wireless micro sensors to collect physical data from the surrounding environment, contributing to sustainability efforts. The gathered data is then transmitted to a central sink sensor device for processing. However, given that DSDN devices operate on limited battery power, their energy constraints significantly impact both the network's lifespan and environmental sustainability. This study aims to enhance the energy efficiency of the Engroove Leach (EL) protocol to extend the network's operational duration while minimizing energy consumption. Clustering and routing strategies are commonly employed to achieve this goal. In this research, the Meta Inspired Hawks Fragment Optimization (MIHFO) system, incorporating passive clustering, is used for clustering purposes. Cluster heads are selected based on criteria such as residual energy, distance to neighbours and the base station, DSD degree, and DSD centrality. Additionally, the Heuristic Wing Antfly Optimization (HWAFO) algorithm determines the optimal path between cluster heads and the Base Station (BS) by considering factors like distance, residual energy, and DSD degree. Evaluation metrics for this study include the number of active DSDs, energy consumption, and data packet transmission to the base station. [15]. Traditional routing protocols in DSDNs frequently face challenges due to high temporal redundancy in data collected at fixed intervals, leading to excessive energy consumption. To address this issue and encourage energy conservation in sensor networks, a practical solution involves employing prediction-based data fusion methods. This work introduces the Low Energy Adaptive Clustering Hierarchy-Energy-Kopt-N (LEACH-Energy-Kopt-N) algorithm, designed to optimize the cluster-head selection phase of the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol. Additionally, the work proposes a data collection model that utilizes data prediction techniques, specifically the Grey Data Prediction Model, to enhance efficiency in sensor data aggregation and transmission [16].

The efficiency of routing algorithms implemented in DSDNs significantly impacts their potential for conserving energy. Developing distributed clustering algorithms presents a challenge as they must efficiently form groups without relying on centralized information gathering. This requires striking a balance between cost-effectiveness, computational complexity, and flexibility while operating within resource constraints. In this study, we introduce a novel hierarchical and distributed approach by integrating the Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm with the Analytic Hierarchy Process (AHP). Our approach involves sensor devices (DSDs) maintaining a matrix that includes potential threshold values representing the probability of serving as the cluster head. These values, determined through AHP, consider both energy and distance conditions relative to the Sink as criteria, with importance levels assigned from 1 to 9. AHP computations, weighted with factors expressing preference for the energy criterion, yield threshold values that minimize energy consumption and maximize packet transmission to the Sink. This method enables DSDs to autonomously determine their cluster head probability based on energy status and distance to the Sink, eliminating the need for centralized control. Compared to algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), our proposed method requires minimal computational resources and can be implemented in a distributed manner [17]. Localization remains a significant challenge in DSDNs in recent years. Accurately assessing and monitoring data collected using beacons and localization methods to DSD locations poses difficulties. Developing effective algorithms like "Distance-Vector-Hop (DV-Hop)" is essential to address this challenge. Such studies aim to enhance DSD localization accuracy by refining the calculation of average hop-size with beacon assistance, thereby reducing localization errors associated with distance measurements between DSDs and beacons. The current research leverages DSD-based Internet of Things (IoT) network deployment and a customized routing protocol based on clustering to improve performance and security. The proposed routing protocol, named Cluster-Based Routing Protocol with Static Hub (CRPSH), thoroughly discovers all potential paths before utilizing them. Simulation results demonstrate that the proposed method achieves superior localization accuracy compared to DV-Hop and other DSDNs are commonly deployed in remote and inaccessible areas to gather data autonomously and transmit it to a central base station. Hierarchical routing protocols are often used in these networks to manage data transmission efficiently. One prominent protocol is the Low Energy Adaptive Clustering Hierarchy (LEACH), which involves two main phases: the setup phase and the steady phase. This study proposes enhancements to the Enhanced LEACH protocol to achieve a balanced energy consumption across the DSDN and extend the lifespan of DSDs. The Enhanced LEACH protocol employs a clustering approach to reduce communication overhead between DSDs and the base station. This clustering scheme aims to optimize energy efficiency by organizing DSDs into clusters with designated group heads to coordinate communication. By selecting group heads based on residual energy levels, the protocol aims to minimize energy depletion and maximize resource utilization within the DSDN [19].

Existing methodologies like LEACH rely on random number-based criteria for selecting group heads in DSDNs. Each DSD generates a stochastic variable, which is then compared to a predetermined threshold value. If the generated value exceeds this threshold, the DSD becomes a group head. However, this approach assumes DSD homogeneity, where all devices have similar structures and energy levels. Consequently, group head selection becomes arbitrary, resulting in an uneven distribution of group heads throughout the DSDN. To overcome this limitation, this paper proposes a new methodology for identifying group heads based on the maximum residual energy of DSDs. This approach aims to optimize energy usage and extend the DSDN's lifespan by selecting group heads with higher energy reserves [20]. DSDNs consist of multiple sensors distributed throughout the monitoring area. Routing data between these sensor DSDs consumes significant energy, which can impact the network's longevity. Thus, efficient energy usage is essential for maximizing the DSDN's lifespan. Various routing and power-saving techniques have been developed to address this challenge. In this study, we propose a novel approach called MOD-GRASP (Modified Greedy Random Adaptive Search Procedure), which utilizes the GRASP algorithm to optimize energy consumption in DSDNs. The MOD-GRASP protocol focuses on reducing power consumption during data transmission to the base station (BS) in a DSDN. Furthermore, the protocol implements a method for selecting the optimal Group head within the network based on GRASP data. The goal is to improve the network's energy efficiency and prolong its lifespan by optimizing the selection of Cluster Heads using the GRASP algorithm [21]. With the progress of drone technology, autonomous unmanned aerial vehicle (UAV) swarms are increasingly employed in various sectors such as traffic management, pollution monitoring, package delivery, and security surveillance. This study presents an enhanced version of the LEACH algorithm tailored for UAV swarm communication in urban environments. Our approach involves selecting group heads based on attributes including group size, distance from the base station (BS), battery percentage, and line-of-sight (LOS), aiming to improve packet delivery efficiency and extend system operation. The method makes use of a two-level hierarchy where cluster heads are selected using the enhanced LEACH algorithm from a designated pool of parent drones (PDs) [22]. Designing a robust routing protocol for DSDNs requires scalability to be a key consideration. As DSDNs gain prominence, applications demanding real-time and continuous data delivery encounter challenges related to power, storage capacity, and energy efficiency. It is crucial to account for these constraints when choosing a routing protocol for DSDNs. Routing protocols can be categorized based on their attributes and the specific types of DSDNs they support. Various performance metrics are utilized to evaluate the efficacy of routing protocols. By conducting such studies, we can analyse the performance of different routing protocols and iterate on them to achieve optimal functionality. [23].

In DSDNs, the energy capacity of sensor nodes is critical as it serves as their primary energy source. grouping DSDN has emerged as a fundamental strategy in DSDNs to conserve energy and extend the network's lifespan. The energy used during data transmission depends on the distance between transmitter and destination nodes, emphasizing the importance of grouping DSDN. This paper introduces a novel fuzzy logic model for selecting group heads, a crucial step in grouping DSDN within DSDNs. The proposed model evaluates five characteristics to determine each node's suitability for group head status, including proximity to the base station, node density, topographical suitability, and remaining power. Using fuzzy logic, we propose the Fuzzy Reasoning-based Energy-Efficient grouping DSDN for DSDNs (FL-EEC/DSDN), focusing on minimizing the distance between CHs. Additionally, we assess the energy distribution efficiency among sensors within the DSDN using the Gini index as a metric for energy consumption in clustered methods. Comparative evaluations between our FL-EEC/DSDN approach and existing methods, including LEACH and other fuzzy logic-based grouping DSDN approaches, demonstrate significant improvements in energy efficiency, network longevity, and balanced energy consumption across sensor nodes of varying network sizes and topologies, as shown through simulation results [24]. Energy limitations present significant challenges in DSDNs, affecting DSDN lifespan and overall performance. Researchers are actively exploring strategies to optimize energy usage while extending the longevity of these networks. Factors such as environmental conditions and routing methods directly impact battery consumption in sensor DSDs. Various quality of service (QoS) metrics are employed to evaluate DSDN performance and minimize battery usage at the routing level. Numerous routing protocols have been proposed to address energy constraints in WSNs. In this study, we conducted an analysis of two low-power protocols—LEACH and Sub-cluster LEACH—and compared their performance. The authors have implemented Levenberg-Marquardt neural networks (LMNNs) and Moth-Flame optimization to enhance DSDN performance. QoS indicators including energy efficiency, end-to-end latency, throughput, and packet delivery ratio (PDR) were evaluated to assess performance. Our simulations revealed that Sub-cluster LEACH with Moth-Flame optimization demonstrated superior DSDN efficiency and effectiveness compared to competing algorithms. [25]. In DSDNs, grouping is a fundamental technique that groups sensor DSDs into DSDN group managed by designated cluster heads to enhance DSDN efficiency and coordination, facilitating data transmission to the sink node. The LEACH protocol is well-known for its effectiveness in enabling efficient grouping in wireless sensor networks. Another approach, termed balanced cluster formation, strives to create DSDN group of equal size with a degree of overlap between them. The work introduces a novel hybrid DSD reconfiguration scheme called Energy-efficient Uniform Size grouping (EUSC), designed to balance the load, improve DSDN lifespan, maintain uniform cluster sizes, and prevent cluster overlap in wireless sensor networks. The EUSC scheme aims to optimize DSDN performance by efficiently organizing sensor DSDs into DSDN group with uniform sizes, thereby enhancing energy efficiency and overall DSDN operation [26]. A significant issue in large-scale dense DSDNs is the efficient utilization of energy resources. With a higher number of DSDs in these DSDNs, there's a greater likelihood of redundant data transmission. To address this, energy conservation becomes paramount, making data fusion and aggregation essential. Aggregating surplus data at intermediary DSDs helps minimize connectivity costs and energy consumption by reducing the number of messages exchanged between sensor DSDs. In this context, the proposed study employs the In-Network data collection and energy-saving protocol, LEACH, to conserve resources in DSDNs. However, ensuring the security and integrity of aggregated data during routing poses a considerable challenge. To tackle this issue, one approach is to identify malicious DSDs within clusters by assessing the confidence value between group heads and group members based on their DSD identities. This helps enhance the protection and reliability of the aggregated data transmission process [27]. Energy efficiency is a crucial consideration in DSDNs. This work proposes an approach that leverages Delaunay triangulation to optimize the deployment of DSDs. By utilizing Delaunay triangulation for placing mobile DSDs, we introduce a clustering method called Equi-Quadrant Division-based Clustering to enable efficient shortest path routing to the base station (BS). This approach addresses challenges such as coverage gaps and the identification of a DSD's sensing range in a random distribution, ultimately enhancing the overall engagement and performance of DSDs in the DSDN [28]. DSDNs have gained widespread popularity due to their affordability, adaptability, scalability, and suitability for deployment in various environments. Energy efficiency has emerged as a crucial design consideration to ensure the longevity of these networks. The LEACH routing protocol has become a standard choice for power-aware DSDNs. However, a notable drawback of LEACH is the premature depletion of energy in base station nodes, leading to a decrease in network lifespan. To address this issue, a modified version of LEACH, known as Modified LEACH (MLEACH), has recently been proposed. MLEACH aims to reduce average energy consumption, thereby extending the network's lifespan. It achieves this by assigning an expiration time to each cluster, reducing the formation of redundant clusters, and minimizing energy expenditure. Additionally, MLEACH mitigates packet loss by eliminating the need for base station reset times. Moreover, it designates a supervisor node within each cluster to monitor routing overhead and facilitate efficient data transmission, thereby preventing the formation of lengthy transmission chains [29]. In DSDNs, DSDs encounter constraints such as limited energy supply, communication range, and computational capabilities. Efficient data routing is essential to help Distributed Sensor Devices (DSDs) conserve energy, thereby improving the overall DSDN lifespan. Clustering protocols play a vital role in achieving energy preservation in DSDNs. These protocols involve selecting group head DSDs based on factors directly impacting DSD power consumption. This paper presents a novel algorithm called Fuzzy-based Zone-group Heads Selection for Heterogeneous Wireless Sensor Networks (FZCHS). By utilizing an optimization fuzzy logic approach, critical factors influencing DSD lifespan are identified and integrated. group heads are chosen based on two key factors: the number of neighbouring DSDs and a novel component representing the potential lifespan of DSDs acting as group heads. This approach aims to optimize energy usage and extend the DSDN's lifespan by efficiently selecting group heads. [30].

III. MACHINE LEARNING Based Cluster Head Selection, Cluster Formation and Path Formation

A DSDN has various objectives, one of which is to ensure comprehensive coverage of the monitored area. It serves multiple purposes such as tracking devices or detecting enemy intrusion in military applications. To optimize the battery life of the DSDs, they can be organized into a set known as the cover set.

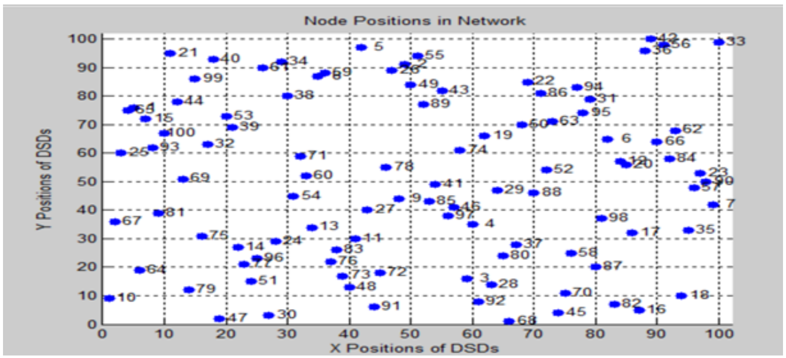

Fig 1: Placement of DSDs in a Network

DSDs within this cover set can be dynamically switched between different operational modes, such as ON or OFF, to enhance health monitoring and improve tracking efficiency. DSDNs can be categorized into single-area DSDNs or multiple-area DSDNs. In a single-area DSDN, all DSDs are distributed within a specific region, whereas in a multiple-area DSDN, DSDs are spread across several groups or locations. For communication between DSDs belonging to different areas, a Head DSD is selected for each area to facilitate inter-location communication.

A. Single DSDN Network

The work is on managing a single-group DSDN. Consider a single DSDN network formed with 100* 100 dimension as shown in the figure 1. There are 100 DSDs spread with horizontal limit between 1 to 100 and vertical limit between 1 to 100. Each of the DSD is represented by its own unique ID and have their own positional information. DSD-21 the position of DSD has a positional value {5,95}. DSD-10 has a positional value of {1,10}. In a similar way all remaining 98 DSD's have their own position. The Single Group DSD Formation is done using the algorithm given in Figure 2.

Process 1: Single DSDN Formation

Data Input: N_n, x_S, x_E, y_S, y_E

Data Output: Location and Identity Matrix

Details:

$k = 1$

$k : 1 ---> N_n$

The horizontal position of DSD is varied between $x_S \ to \ x_E$ which can be defined as

$$x_k = xv \ any \ xv \ which \ satifies$$

$$x_S \le xv \le x_E \ \& \ xv \ne x_{his}$$

The vertical position of DSD is varied between $y_S \ to \ y_E$

$$y_k = yv \ any \ yv \ which \ satifies$$

$$y_S \le yv \le y_E$$

$$x_{His} - history \ of \ one \ dimension \ previously \ assigned$$

&

and $yv \ne y_{His}$ $y_{His} - history \ of \ other \ dimension \ previously assigned$

e) The map is created with DSD identity as key and value as position

$(k, (x_k, y_k))$

f) Form the k^{th} row matrix

DSD Identity	Location of DSD
k	(x_k, y_k)

Fig 2: Single DSDN Formation

B. Multi Group DSDN Network using Machine Learning

For a Multi Group DSDN Network. Each level is associated with a group of DSDs associated with it. The formation of Groups will be done on the basis of k means algorithm. The algorithm used falls under the category of unsupervised machine learning. The grouping is done based on similarity of data. The partition depends upon the tuning parameter K. Where K defines the number of groups. The various phases of K means grouping for DSDN can be defined as follows

1. **Set Up Phase** The position of group centre is chosen in a random fashion. The number of such group centres depends upon the tuning parameter K.
2. **Labelling Phase** From each of the DSD to the initial centre of the group the distance is computed using Euclidean concept. After computing k distances with respect to the centroids the lowest distance is found and DSD is assigned a Group DSDN label. Each DSD is assigned to only one Group. Figure 3 shows the K means DSDN Network with six different groups. The orange color indicates the shift in the cluster centroids positions while grouping the DSDNs in an optimized fashion based on distances

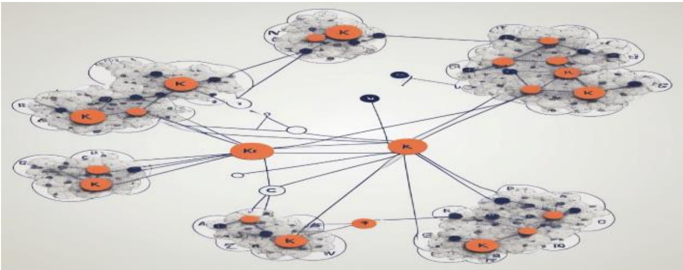

Fig 3: K means DSDN Network

. 3 **Optimization Phase** In the optimization phase the position of each group DSDN centre is recomputed based on assigned DSDs. The new position of centre for each group is computed using a mean formula applied on each of the DSD's in the group. The algorithm for Group DSDN formation is summarized in Figure 4

Algorithm
Multi Group DSDN Formation using K Means
Input

$$L_{dsd} = (x_{dsd1}, y_{dsd1}) \dots (x_{dsdn}, y_{dsdn})$$

Where,

$$L_{dsd} = Location\ for\ the\ DSD$$
$$x_{dsd1} = x\ dimension\ for\ 1^{st}\ DSD$$
$$y_{dsd1} = y\ dimension\ for\ 1^{st} DSD$$
$$x_{dsdn} = x\ dimension\ for\ n^{th}\ DSD$$
$$y_{dsdn} = y\ dimension\ for\ n^{th}\ DSD$$

Result:
Group Label assignment for the DSDs
Process

A. Set Up Phase

Randomly choose N values from L_{dsd} as the initial Group DSDN centroids

B. Group Label Assignment Phase

1. Assign each DSD to the nearest centroid μ forming N DSDN Groups {G1, G2, ...GN}

$$G_n = \{L_{dsd}: \|L_{dsd,m} - \mu_i\|^2 \leq \|L_{dsd,m} - \mu_n\|^2\ for\ all\ n, 1 \leq n \leq Ng$$

2. Recalculate the centroids based on mean value

$$\mu_{gk} = \frac{1}{|G_{gk}|} \sum L_{dsd,i} \quad L_{dsd,i} \in G_{gk}$$

3. Repeat steps until convergence, where convergence occurs when the centroids no longer change significantly or a maximum number of iterations is reached
4. The final result is a partition of the DSD L_{dsd} into N different groups {G1, G2, ...GN} Where each DSD will belong to a Group DSDN which has nearest mean.

Fig 4: Group DSDN Network

C. Group Head DSDN Selection

The Group Head DSD plays a unique role in facilitating group communication and inter-group communication within a DSDN. The selection of a Group Head DSD should take into account factors such as energy dissipation, battery level, DSD position in the DSDN, DSD mobility, and the buffer or load present in the DSD. Considering these parameters is crucial for improving the overall lifetime performance of the DSDN.

The Group Head is selected alternatively with a combination of Random Forest and Support Vector Machine algorithm.

Random Forest is a popular ensemble learning method used in machine learning for classification and regression tasks. It operates by constructing multiple decision trees during the training phase and then combining their predictions to make a final decision.

1. **Data Collection DSDN Phase**

   During the Data Collection phase of a DSDN, the Base Station is utilized to gather information from DSDs regarding various features such as battery level, distance from the base station, average mobility, and buffer levels.

2. **Initial Group DSDN Head Computation**

During the Data Collection phase of a Wireless Sensor Network, the Base Station is utilized to gather information from DSDs regarding various features such as battery level, distance from the base station, average mobility, and buffer levels.

3. **History Capture and Training Algorithm**

Train multiple decision trees on different subsets of the training data and features. Each decision tree is trained independently.

During the training process, each decision tree considers a random subset of the features to split the data at each DSD. This randomness helps in reducing overfitting and improving the generalization of the model.

As each decision tree is trained, it learns to classify DSDs in DSDN as potential cluster heads or non-cluster heads based on specific features. These features include battery level, distance between the node and the Base Station, mobility of DSDs in the DSDN, and remaining buffer level of DSDs in the DSDN.

In the context of selecting DSDN heads in a DSDN Network, Random Forest utilizes multiple decision trees, each analysing a random subset of sensor data to determine suitable candidates for DSDN head positions. By aggregating the decisions of these individual trees, Random Forest identifies sensors that are frequently chosen across the ensemble as potential DSDN heads. This collective decision-making process leverages the diverse perspectives of the individual trees, akin to seeking advice from a group of experts, resulting in an effective selection of DSDN heads for the DSDN network.

In a similar fashion the Group DSDN head selection process undergoes Support Vector Machine execution as well.

Imagine you have a bunch of points on a graph, and you want to draw a line to separate them into two groups. But here's the twist: these points aren't just randomly scattered; they're also labelled with different categories, like high performing DSD and medium performing DSD.

Support Vector Machines (SVMs) are powerful tools designed to determine the optimal decision boundary between different groups of points. Rather than simply drawing a line, SVMs identify the line that maximizes the separation (or gap) between these groups of points. This gap is crucial because it enhances the model's ability to accurately classify new, unlabelled points based on their position relative to the decision boundary. For each of

DSDs the features history is fed as a training data and then the DSDs are classified into High Performing and Low Performing DSD. The high performing DSDs are filtered out.

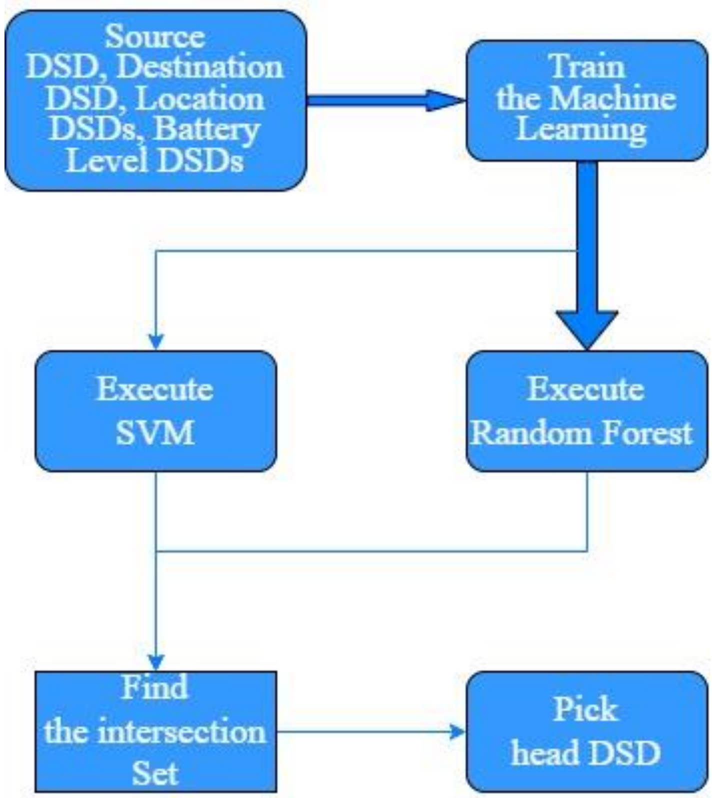

Fig 5: Head DSD Selection Process

Finally, an intersection set is created between random forest and Support Vector Machine which will produce the common DSDs. One of them will be chosen as head DSD. Figure 5 shows the short summary of head DSD selection process. The location, battery level and other features are taken as an input for the process. Random Forest and Support Vector Machine are executed and then a set of DSD's are found out. The first set is called Random Forest DSDs, the second set is called Support Vector Machine DSDs. The intersection between the two sets will provide an optimized set of DSD's and then one of them is chosen as a head DSD.

D. End to End Data Transfer Link

The Path Formation Process involves establishing the end-to-end path between nodes in a network. Initially, the source DSD checks if the destination DSD is within the same group; if so, a direct link is established. If the source and destination nodes belong to different groups, the source DSD locates its group head and establishes a link to the head DSD of its group in the Distributed Sensor Device Network (DSDN). The source head DSD then initiates a Route Request (RREQ) packet to all group head nodes. The group head nodes respond with a REPLY indicating which DSD has the destination. Finally, the destination DSD establishes a link to complete the path.

IV. COMPARISON ALGORITHMS NOTES

This section describes LEACH and ELEACH method which are present in the literature and is used for performance analysis with the proposed method.

A. LEACH

The LEACH method involves selecting head nodes randomly and probabilistically within each group of the Multi-group DSDN. Once head nodes are selected, the path establishment process begins with the initiator DSD transmitting data to its chosen head DSD. The communication then progresses from the head DSD to the base station, which sequentially scans through each group until reaching the intended destination DSD.

B. ELEACH

ELEACH, similar to LEACH, divides the DSDN into multiple segments and uses path construction and head DSD selection for data transmission. In ELEACH, the choice of head DSD considers factors such as battery level and distance from the base station, aiming to improve network lifespan compared to LEACH. However, ELEACH still faces challenges related to throughput and link count because it relies on LEACH for data delivery.

V. RESULTS

The following section describes the results of proposed Machine Learn based Group DSDN method (ML-DSDN) comparison with existing methods LEACH and ELEACH.

Table1: Simulation Input

Parameter Name	Parameter Value
Number of Group DSDN	6
Group 1 End Points	Xdsdmin=1 Ydsdmin=1 Xdsdmax=50 Ydsdmax = 50
Number of DSDs Group1	5
Group 2 End Points	Xdsdmin=51 Xdsdmax=100 Ydsdmin= 1 Ydsdmax = 50
Number of DSDs Group2	10
Group 3 End Points	Xdsdmin=100 Xdsdmax=150 Ydsdmin= 1 Ydsdmax = 50
Number of DSDs Group3	10
Group 4 End Points	Xdsdmin=1 Xdsdmax=50 Ydsdmin= 51 Ydsdmax = 100
Number of DSDs Group4	5
Group 5 End Points	Xdsdmin=51 Xdsdmax=100 Ydsdmin= 51 Ydsdmax = 100
Number of DSDs Group5	5
Group 6 End Points	Xdsdmin=101 Xdsdmax=150 Ydsdmin= 51 Ydsdmax = 100

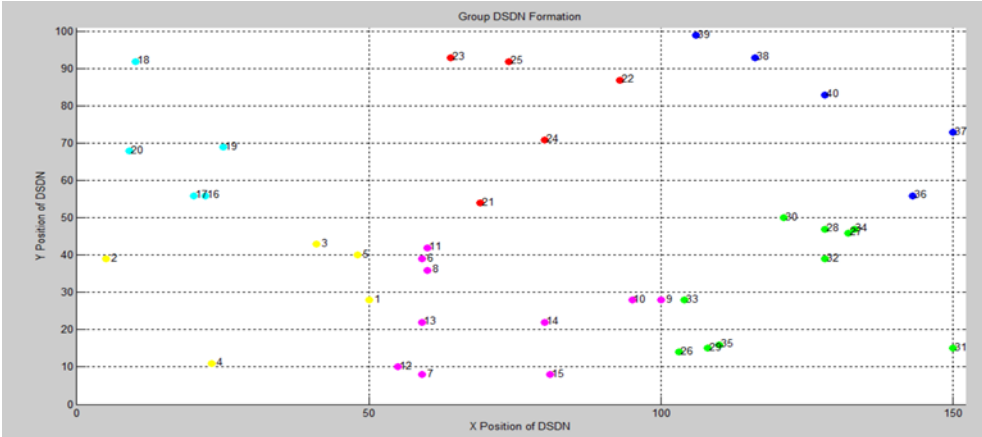

Fig 6: Group DSDN Network

Figure 6 shows the Group DSDN Network with one axis as X dimension and another dimension is of Y. First Group has set of DSDs namely {DSD-1, DSD-2, DSD-3, DSD-4, DSD-5}, The Second Group has set of DSDs namely {DSD-6, DSD-7, DSD-8, DSD-9, DSD-10, DSD-11, DSD-12, DSD-13, DSD-14, DSD-15}, The third Group has set of DSDs namely {DSD-16, DSD-17, DSD-18, DSD-19, DSD-20}. The fourth Group has set of DSDs namely {DSD-21, DSD-22, DSD-23, DSD-24, DSD-25}. The fifth Group has set of DSDs namely {DSD-26, DSD-27, DSD-28, DSD-29, DSD-30, DSD-31, DSD-32, DSD-33, DSD-34, DSD-35}. The sixth Group has set of DSDs namely {DSD-36, DSD-37, DSD-38, DSD-39, DSD-40}. Each DSDs have their own boundaries in the DSDN network.

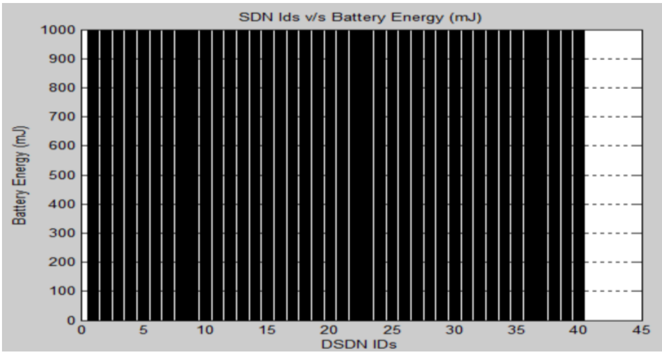

Figure 7: Battery Level DSD's

Figure 7 shows the battery level for DSD's. All the 40 DSD's have been initialized with 1000 J.

A. End to End Delay

The time taken for DSDN route formation refers to the duration it takes for the Route Request (RREQ) to travel from the S-DSD to the D-DSD, and then for the Path Formation Reply (RRPLY) to return from the D-DSD to the S-DSD.

$$DSDN(delay) = RP_{stop} - RQ_{start}$$

$$Where,$$

$$RP_{stop} = Time\ taken\ for\ getting\ REPLY\ packet$$

$$RQ_{start} = Time\ taken\ for\ sending\ RREQ\ packet$$

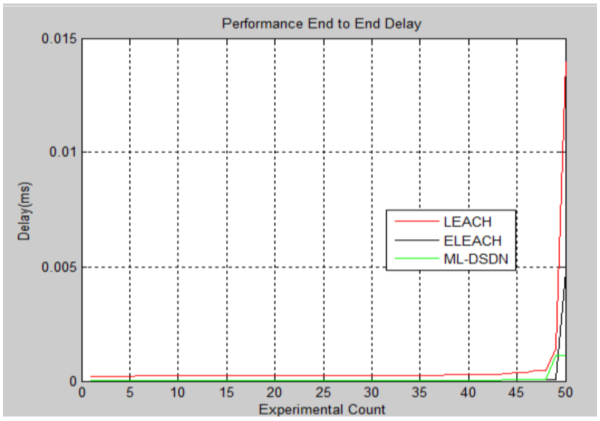

Fig 8: End to End Delay

Figure 8 shows the end-to-end delay comparison between proposed ML-DSDN with LEACH and E-LEACH method. From the fig it is evident that the ML-DSDN is having the lowest value across all experimental count. As the experimental count increases the delay also increases. The maximum value of delay for ML-DSDN is 0.003 whereas for E-LEACH has the maximum value of delay with a value of 0.004 and then for LEACH the value of maximum delay with a value of 0.014. Hence ML-DSDN has the best performance.

B. Hops Performance

The count of set of links between source DSD to destination DSD

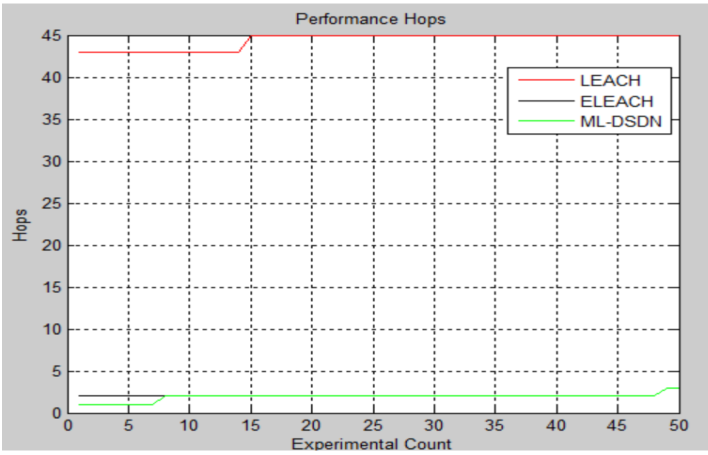

Fig 9: Hops Performance

Figure 9 shows the hops performance. From the figure 9 it is evident that ML-DSDN has the lowest hops followed by ELEACH and LEACH. LEACH has the maximum hops.

C. Total Energy Consumption

The dissipation consumption for entire FDP route can be defined as be

$$TDC = \sum_{k=1}^{Nfdppair} D_c\,(k)$$

$$Where,$$

$$Nfdppair = Numberof\ Pair\ of\ FDPd\ in\ path$$

$$D_c(k) = Dissipation\ \ consumed\ \ across\ k^{th}\ \ link$$

The dissipation consumed by the k^{th} pair given by

$$Ec = 2E_{txpair} + E_{genpair} d(S - DSD, D - DSD)^{\delta f}$$
$$E_{txpair} = energy\ required\ \ for\ \ transmission\ of control\ packets\ of\ DSD\ pair$$
$$E_{genpair} = energy\ required\ for\ packet\ generation\ of\ DSD\ pair$$
$$d(S - DSD, D - DSD) = dis\tan c\, e\ between\ FDPs\ \ Source\ FDP\ and\ destination\ FDP$$
$$\delta f\ = attunuation factor\ \ \ 0.1 \leq \delta f \leq 1$$
$$E_{genpair} \prec\prec E_{txpair}$$

Figure 10 shows comparison with respect to . ML-DSDN has the lowest energy consumption followed by E-LEACH and LEACH.

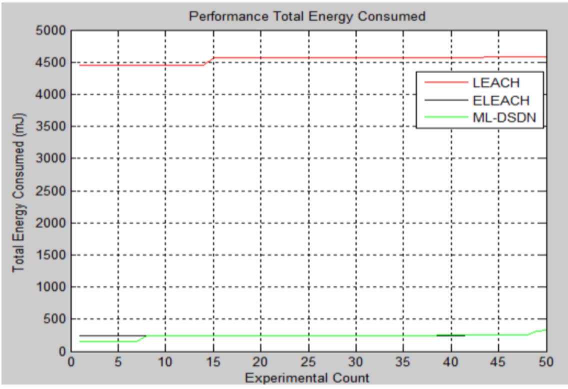

Fig 10: Total Energy Consumption

The maximum value of energy consumption for ML-DSDN is below 500 mJ compared to LEACH which has maximum value of energy consumption above 4500 mJ.

D. Alive DSD Count

The alive DSD count is count of set of DSDs whose value is higher than or equal to reduced value of $1/4^{th}$ of initial battery level.

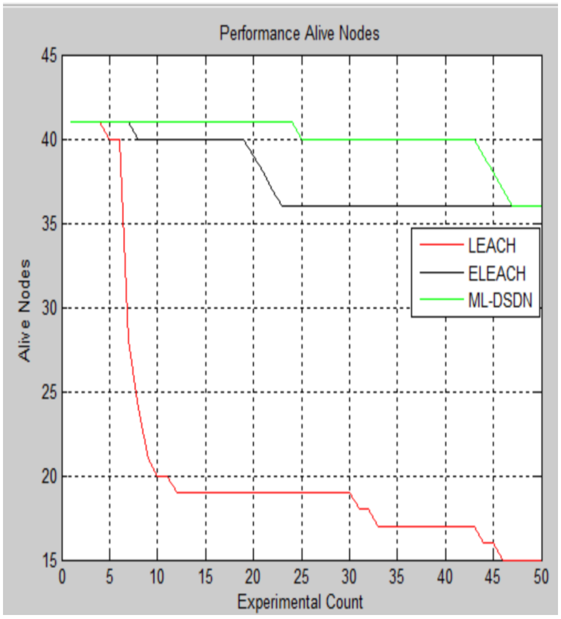

Fig 11: Alive DSDs Count

Figure 11 reveals the alive DSDs count. ML-DSDN has the highest alive DSDs followed by ELEACH and LEACH. As the experimental count increases the value of alive DSDs decreases.

E. Dead DSDs Count

The Dead DSDs count is obtained by taking the difference between total DSDs to the alive DSDs

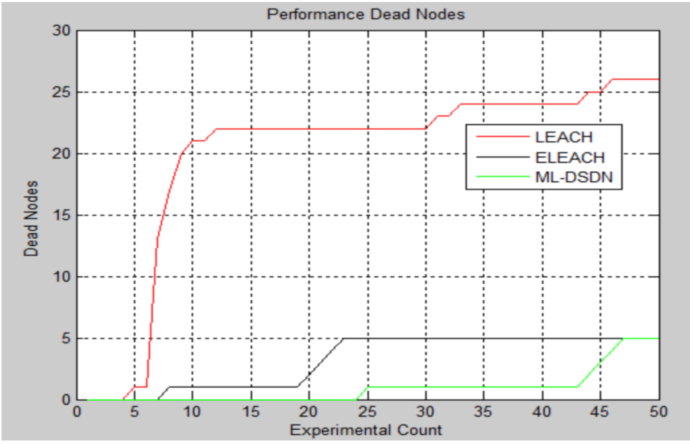

Fig 12: Dead DSDs Count

Figure 12 shows the dead DSDs count. As the experimental count increases the count of dead DSDs also increases. The lowest dead DSDs are for ML-DSDN followed by E-LEACH and LEACH. At the experimental count 6 the dead DSD count for ML-DSDN is 0, ELEACH is 1 and LEACH is 20. For the experimental count 25 the dead DSDs for ML-DSDN is 1, ELEACH is 5, LEACH is 22.

F. Lifetime Ratio

The division performed between Alive DSDs to Dead DSDs

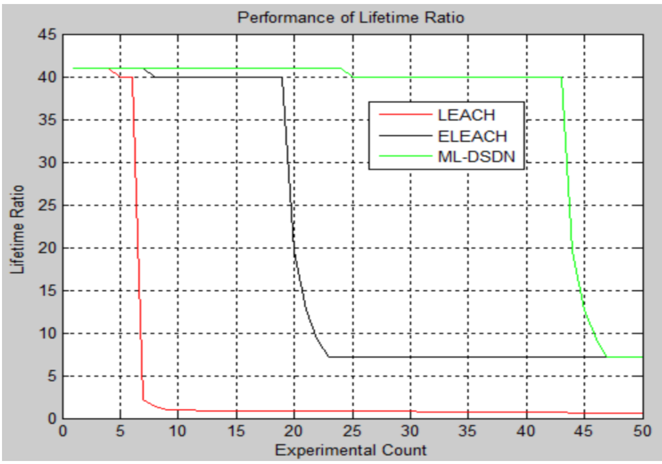

Fig 13: Lifetime Ratio

Figure 13 shows the lifetime ratio comparison. ML-DSDN has the highest lifetime ratio followed by ELEACH and LEACH. As the experimental count increases the lifetime ratio decreases.

G. Routing Overhead

The ratio is computed using the count of RREQ and REPLY packets in the denominator and then number of data packets sent on the numerator. If the overhead value is on the lower side then performance of the algorithm is better.

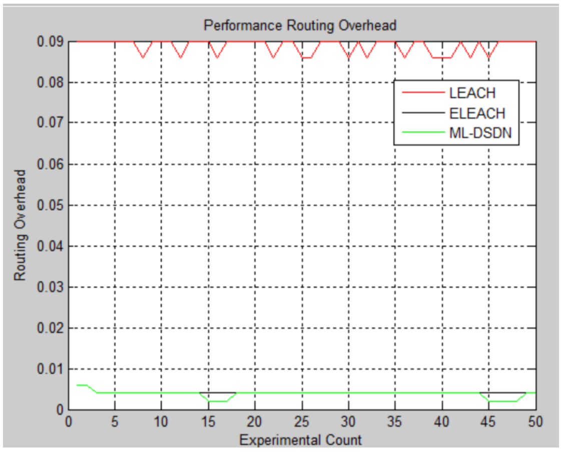

Fig 14: Routing Overhead

Figure 14 shows the routing overhead for all the algorithms. ML-DSDN has the lowest routing overhead compared to ELEACH and LEACH. The LEACH is having highest routing overhead hence performance of LEACH is less.

H. Throughput

The throughput is measured by sending data packets over a period of time.

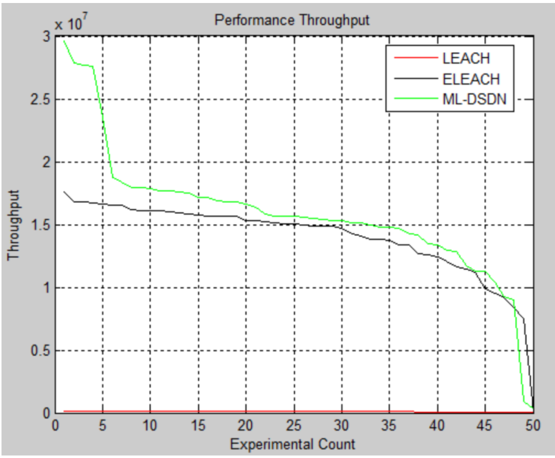

Fig 15: Throughput Measure

Figure 15 shows the throughput measure. As the experimental count increases the throughput measure decreases. For most of the iterations the ML-DSDN have the highest throughput followed ELEACH and LEACH has the lowest throughput.

I. Residual Energy of Network

The residual energy of network is computed by summing out remaining battery energy level.

$$REN = \sum_{i=1}^{\mathrm{N_{DSDs}}} \mathrm{RE(DSD)_i}$$

Where,

$\mathrm{N_{FDPs}}$ = total number of DSDs

$\mathrm{RE - DSD_i}$ = Re s idual Energy for $\mathrm{i^{th}}$ DSD

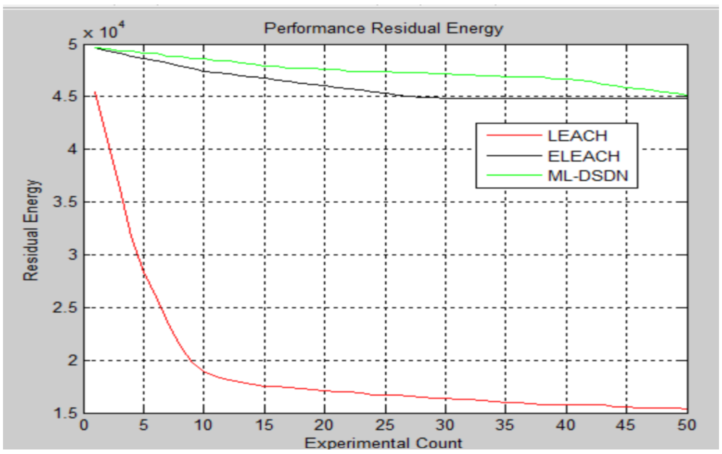

Fig 16: Total DSDN energy of DSDN Network

Figure 16 shows the DSDN energy of DSDN Network. As the experimental count increases the residual energy decreases. ML-DSDN is having highest DSDN energy as compared to ELEACH and LEACH. Across all experimental counts ML-DSDN have the highest DSDN energy.

Table 2: Performance Comparison

Parameter	ML-DSDN Improvement Percent with LEACH	ML-DSDN Improvement Percent with ELEACH
Delay	73.91 %	12.91%
Hops	89.68%	1.02%
Energy Consumed	87.26%	0.007%
Alive DSDs	23.76%	1.5%
Dead DSDs	72.85%	4.8%
Lifetime Ratio	51.61%	25.76%
Routing Overhead	89.68%	13.98%
Throughput	51.1%	2.8%
Residual Energy	28.3%	0.09%

The percentage improvement of ML-DSDN compared to LEACH and ELEACH is summarized in Table 2. From the Table 2 it is evident that performance of ML-DSDN is better compared to existing methods.

From all the comparison results it is evident that ML-DSDN is performing the best compared to ELEACH and LEACH method.

V. CONCLUSION

First, we have described the DSDN network in which DSDs are placed, this was followed by Group DSDN network. The existing methods which are based on LEACH and machine learning are also described. This is followed by proposed method ML-DSDN with DSDN formation, Group DSDN formation, selection of head DSDs by making use of multiple machine learning algorithms and end to end path formation for DSDs. The comparison methods namely LEACH and ELEACH are also described in a short format. The proposed method ML-DSDN is compared with LEACH and ELEACH for various parameters namely end to end delay, hops performance, energy consumption, alive count, dead count, lifetime ratio, routing overhead and throughput measure and from the experiment it is proved that ML-DSDN is working the best.

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