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Original Article

Efficient Sensors Deployment and Reliable Data Collection using PSO-based Dynamic Clustering Approach in UAV-Assisted LoRaWAN

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Abstract - *In recent times, utilizing Unmanned Aerial Vehicles (UAVs) has proven to be an effective method for gathering data for environmental monitoring in inaccessible locations lacking infrastructure. This has resulted in numerous valuable studies being conducted in this area. However, collecting data from sensor nodes using UAVs has posed a challenge due to the potential impact on the UAV's communication and flight time. Mainly to improve the deployment and data collection efficiency of the sensors in this article, Efficient Sensors Deployment and Reliable Data Collection using PSO-based Dynamic Clustering Approach (ESRD-PDCA) is developed in the UAV-assisted LoRaWAN-based network. The two main categories of the proposed ESRD-PDCA are UAV network construction, efficient sensor deployment, LoRaWAN routing protocol, and Particle Swarm Optimization (PSO) based dynamic clustering approach. With the presence of these processes, the network's overall quality and reliability are improved, leading to efficient communication among the sensors. The implementation of the proposed UAV-assisted LoRaWAN is constructed using the software NS2. The parameters that are calculated for the performance analysis of the proposed approach are data completion time, energy efficiency, and reliability.*

Keywords - *Unmanned Aerial Vehicles (UAVs), Efficient Sensors Deployment, Reliable data collection, Particle Swarm Optimization (PSO), Dynamic clustering approach, LoRaWAN based network.*

1. Introduction

Unmanned aerial vehicles, or UAVs, are showing promise as a technology for a wide range of wireless communication [1]. These vehicles are versatile and available in many sizes, making them ideal for various applications, including live streaming, military missions, delivery services, monitoring urban traffic, and disaster relief. UAV networks operate in Three-Dimensional (3D) spaces and are self-organized, decentralized, and operating without infrastructure. They use capabilities present in Vehicular Ad-hoc Networks (VANET) and Mobile Ad-hoc Networks (MANET) to gather data from various areas and send it via communication links to its intended destination [4]. UAV ad-hoc networks operate in a 3D environment; therefore, tracking their locations, motion, and direction is essential. Consequently, several routing protocols have been implemented to improve UAV ad-hoc network performance [2]. The effectiveness of many UAVs' communications is directly impacted by these protocols. Routing tables are used by traditional topology-based routing protocols to forward data packets via the shortest path, which is usually measured hop by hop [3]. However, given the fast speed at which UAVs move, this approach requires extra overhead for route discovery and is not suitable for supporting the 3D nature of UAV networks. Position-based routing methods use additional geographic data from GPS or other position-tracking services to address this problem. According to its position or geographic location, a source UAV node sends data packets to a destination UAV using this method. The drone is equipped with cameras, sensors, communication equipment, and other tools. It was initially designed for military purposes but now also protects borders for civilian use. Unmanned aerial vehicles are commonly utilized in the armed forces. The United States Department of Defense (DOD) began producing unmanned aircraft systems in 2005. Currently, the leading countries in UAV manufacturing are the USA, Israel, China, Iran, and Russia. India's Rustom series of UAVs is currently in development. Creating a UAV is relatively simple and cost-effective compared to other aircraft. These drones are composed of essential elements and can be divided into two categories: Fixed Wing UAVs and Rotatory wing UAVs [5].

1.1. UAV Communication System

UAVs consist of a variety of essential components. Each component serves a specific purpose to ensure successful flight operations, but the most crucial part is the communications systems. UAV operators can accomplish their goals with the help of these systems [8, 9]. They would be necessary for unmanned flight to be considered feasible and for gathering and sharing aerial imagery and communication data. UAV communications systems are becoming increasingly important as they continue to establish themselves as the primary platform for aerial data collecting across various industries. Operators are forced to rely heavily on unreliable and highly adaptive communication technologies in order to collect airborne images and data. Currently, the most sophisticated option for dependable UAV communications systems is RF communications.

In many non-military applications, civilian drones are considered the best choice because of their compact design, low weight, low power consumption, and efficient communication interface. 2.4 GHz and 5.8 GHz are the usual frequencies used by these drones for communication. First-Person View (FPV) video is transmitted on one frequency, while the drone is controlled from the ground on another [6]. This allows for seamless transmission of visuals and data from the drone to those on the ground while it remains in flight. In contrast, military drones have distinct features and purposes, such as longer missions and advanced capabilities for providing aerial visuals of battlegrounds. However, using drones in defense applications raises concerns about signal jamming. To address this issue, some defense drones are equipped with redundant onboard navigation systems that do not rely on GPS data. This minimizes the risk of signal jamming and ensures a safe return to base for these drones, even in challenging situations.

1.2. UAV Communication Design

The strategy focuses on a compact, hand-controlled Unmanned Aerial Vehicle (UAV) with a maximum take-off weight of 7 kilograms. The UAV's purpose is surveillance, monitoring, reconnaissance, and target tracking to assist in operations for both military and friendly forces. Additionally, the UAV will have a well-balanced camera payload [10]. The primary functions of the UAV's communication system are to transmit payload images and flight data for independent intelligence and surveillance missions.

To ensure stealthiness, the UAV's design, color, and minimal heat and noise emissions will be considered. However, due to limited power availability onboard, electromagnetic stealth is not feasible for this lightweight UAV during combat operations. As a preventive measure against attacks on the UAV by hostile entities, countermeasures will be implemented to secure its control and communication systems from data manipulation or interception. This will involve using commercially available frequency-hopping handsets and authentication methods between the UAV and its ground controller [6]. The remaining portions of this paper are arranged as follows: The prior study on data collecting utilizing the clustering approach in UAVs is provided in Section 2. Section 3 provides the proposed algorithm. In Section 4, the proposed algorithm's simulation results and analysis were discussed, along with a comparison with the current routing protocols. The conclusion and recommended subsequent paths are provided in Section 5.

2. Literature Survey

In [11], the authors NF Mohammad et al. proposed an energy-efficient multi-UAV data-collecting methodology for WSNs. The authors design the data collection system as a joint optimization issue of system cost and energy consumption limited by memory size, UAV mission time, and communication power. Two steps are involved in solving the problem: Initially, a triangulation-based K-means clustering that minimizes the number of aggregators employed, and the system cost is used to estimate the position and number of aggregators required. Second, the Gaining-Sharing Knowledge (GSK) optimization technique determines the dock station position, reducing energy usage. Each GSK potential solution's ideal UAV trajectory is created using a Capacitated Vehicle Routing Problem (CVRP) that blends metaheuristic and heuristic solution methods.

In [12], the authors, V Gupta and D Seth developed the 3Dimensional Improvise Clustering Algorithm (3DICA), a revolutionary cluster routing protocol, to address the node uncertainty issue in cluster head selection. The author creates the cluster head and cluster members and then computes the energy usage through transmission. The results of the simulation show that building 3D clusters with the recommended method produces more data in less time. In [13], the authors Liu et al. proposed an effective routing strategy created for UAV-based WSNs over data gathering, addressing the excessive energy consumption and premature SN death of some due to outdated routing protocols.

First, a UAV communication coverage model is developed, and the UAV-WSNs data-gathering architecture is constructed. Second, based on the data transmission channel, the routing region was initially split into air-to-ground and ground-to-ground routing areas. To encourage the balance of energy usage among clusters, a multi-hop routing protocol based on unequal-sized clustering is suggested in light of this. The next step provides a sector dynamic adjustment technique modeled from lottery turntable wheels that simulates a rotation to dynamically adjust member nodes in each cluster and maintain the equilibrium of energy consumption amongst SNs in the cluster. In [14], Zekai Wang said that for coordinated transmission and distribution systems during severe natural catastrophes, use MPDRRM. It suggests using unmanned aerial vehicles and mobile energy storage to sustain vital loads and preserve power balance while restoring the system.

A modified three-level analytical target cascading technique is used to solve the model, broken down into sub-problems concentrating on communication, transmission, and distribution systems. Case studies demonstrate how well this strategy works to improve load restoration and strengthen the transmission and distribution coordinated system's resistance to natural disasters. In [15], an analytical framework is used to assess the timeliness of IoT systems using UAV communications. It comprises AoI analysis, which takes outages into account, as well as outage probability analysis. The paper derives an outage probability formula based on Shannon's theorem by solving a lossy coding problem particular to UAV communication. In order to reduce PAoI, it also calculates the PAoI and optimizes the rate of information creation. Theoretical computations and simulations provide an ideal server usage ratio of 0.5 or below, providing guidance for real-world applications in enhancing the timeliness performance of UAV lossy communication.

In [16], the author Hakim Ghazzai introduced "WaveGAN," a GAN-based approach for optimizing FANETs using mmWave technology. By choosing the best communication paths with the optimum channel conditions, the objective is to maximize the network's throughput. Beam search is then used to modify these network topologies for mmWave-based FANET requirements after WaveGAN first learns to build efficient network topologies from a supervised dataset. Simulation results show that WaveGAN is a viable approach for effective and efficient dynamic FANET deployments, as it can quickly find FANET topologies with low optimality gaps across different network sizes. In [17], an "OLSR+GPSR," an optimized link-state routing scheme tailored for FANETs comprised of UAVs. This novel approach combines OLSR with GPSR to address challenges posed by UAVs' mobility, limited energy, and dynamic topology. In order to maximize routing efficiency, OLSR+GPSR incorporates a fuzzy algorithm to modify the broadcast period of greeting messages based on UAV velocity and position prediction inaccuracy. In contrast to OLSR, MPR node selection in OLSR+GPSR takes into account a number of factors, including energy levels, buffer capacity, neighbor degree, and node stability. Notably, OLSR+GPSR reduces routing overhead by streamlining OLSR's operations by eliminating TC message propagation and full routing path calculations. OLSR+GPSR is effective for FANETs, as demonstrated by simulation findings using NS3, which show it outperforms other approaches like P-OLSR and OLSR-ETX in metrics like delay, packet delivery ratio, overhead, and throughput. In [18], a route planning algorithm for UAV relays addressing connectivity challenges in mountainous terrains is crucial for search and rescue operations. The algorithm comprises two phases: (1) detecting poor connectivity areas, and (2) an energy-aware, resilient path-planning method to optimize coverage links. It employs viewshed analysis to identify visibility between areas of interest and cell towers, creating a blockage map to avoid signal loss zones. This ensures UAV paths avoid areas without coverage while maximizing coverage within energy limits and hazardous weather conditions.

Evaluation with publicly available mountainous datasets validates the method's efficacy in improving communication networks in isolated, difficult settings. In [19], the author proposed that DMMS has described NDN to address the challenge of producer mobility, especially in scenarios involving high-speed and unpredictable movements of UAVs. During handoff, DMMS uses decentralized Anchors to deliver consumer Interest packets proactively to the producer's estimated location. It also presents a new forwarding technique that combines location-based and traditional forwarding strategies to improve efficiency without changing the architecture of the network. DMMS is a viable option for low-latency content delivery in NDN architectures, outperforming other solutions like MAP-ME and Kite through ndnSIM simulations in a realistic situation, displaying superior network cost and user quality-of-service metrics. In [20], the authors introduce a combination method for UAV-LiDAR data-based treetop detection and tree crown segmentation that is being tested for the first time.

Initially, a Dalponte region-growing technique was presented to accomplish crown delineation, and a multiscale adaptive local maximum filter was suggested to identify treetops precisely. The limited region of each tree was then determined using the mean-shift voxelization and super voxel-weighted fuzzy c-means clustering approach, which was based on the coarse-crown result. Finally, precise cloud points for each tree were acquired. In [21], the authors researched an Unmanned Aerial Vehicle (UAV) assisted sensor network system in which data is transmitted to the Base Station (BS) by the near-end UAV after being relayed to it by the far-end UAV. The author suggested an Adaptive UAV-aided sensor network Cooperative Data Acquisition (AUCDA) scheme for such a system, taking into account the Age of Information (AoI) as a measure of data freshness. To split task areas for UAVs, the author first introduces a Gaussian mixture clustering approach based on an ambiguous threshold. Expanding on this, the author presents a diffusion-based relay pairing technique for forming relay connections between UAVs. Lastly, the author suggested using the Multilayer Adaptive Large Neighborhood Search (MALNS) method to create paths for UAVs to return to the Base Station (BS) for charging and paths for data relaying between UAVs. In [22], the authors introduce a dependable and safe architecture for UAV network services that combines deep learning and blockchain to give UAVs safer and more effective network services. To improve the security of UAV communication data transfer, the author suggested a UAV cluster identity management module that combines blockchain, encryption techniques, and digital signatures. Then, to improve the security of the UAV operating environment, the author presented a real-time secure situational awareness system for UAV cluster terminal devices based on deep learning, machine learning, and malicious process detection technologies.

In [23], the authors proposed a productive technique for gathering data with UAV assistance that minimizes the WSN's overall power consumption. First, the ground and aerial layers of a two-layer UAV-assisted data-collecting model are presented. The ground layer is used by the Cluster Members (CMs) to sense the ambient data. The CMs then transfer the data to the Cluster Heads (CHs), who then forward the data to the UAVs. Several UAVs comprise the aerial network layer, which gathers, stores, and transmits data from the CHs to the data center for examination. Second, an enhanced K-Means++ clustering approach is suggested to maximize the quantity and placement of CHs. In addition, an Actor-Critic strategy is presented to maximize the deployment of UAVs and their correlation with CHs. In [24], the challenge of establishing efficient network communication services in IoT networks, especially during natural disasters.

It suggests utilizing UAVs as the primary communication devices in an emergency network's hierarchical multi-domain data transmission architecture. The architecture takes advantage of UAVs' ability to sense network status and learn spatiotemporal connection properties to improve their roles as network controllers and switches. A routing algorithm based on FedRDR is created to increase the generalization of the routing decision model by increasing the number of training data samples. Compared to federated reinforcement learning, simulation results show that the FedRDR algorithm reduces parameter transmission size by around 29%, achieving an average communication data size of about 45.3 KB per domain controller. This approach facilitates knowledge transfer, accelerates intelligent agent training, and lowers communication costs, offering practical benefits for UAV network deployment in resource-constrained and emergency scenarios. In [25], a Network scenario with UAV support for edge computing is used to maximize task delays for edge computing. When the wireless connection between UEs and ECSs is compromised, the UAV acts as a relay node to forward tasks. The joint UE-ECS matching and UAV 3D hovering position deployment optimization problem is converted into a continuous-variable decision process. For this, a collaborative optimization method based on PPO is created. Experimental results show the algorithm achieving seamless rewards after three million training steps, demonstrating desirable convergence. Simulations across various environments confirm the algorithm's effectiveness, consistently achieving lower average latency rates and up to an 8% reduction compared to baseline scenarios.

3. Proposed System

3.1. Proposed ESRD-PDCA Method

The proposed ESRD-PDCA system has been classified into four steps to carry out a full set of operations.

3.2. UAVs Network Construction

In the field of Unmanned Aerial Vehicles (UAVs), Mesh, star, and multi-star are the three primary topologies that are utilized. Mobility, energy, inter-UAV distance, noise, link quality, and path availability are some of the other topologies. Figure 1 shows these are all significant aspects to consider when sending messages from the UAVs to the Ground Station (GS). To achieve optimal communication for UAVs, various mechanisms and strategies have been implemented. Numerous advancements have been made in Flying Ad-hoc Network Technology (FANET), such as routing optimization techniques.

Depending on the particular application, FANET uses various link types, including group, multiple groups, indirect, and direct [8, 13–15]. These links are combined in Figure 2 network design. In addition to indirect links with other clusters (VANET and MANET), the FANET Cluster Head (CH) has direct links with the members of its cluster. There are numerous group connections throughout the entire network. Because of its increased movement, the structure of FANET changes more often than that of MANET and VANET. If a UAV's designated path fails, the corresponding FANET also fails and must be updated. The main issue that disrupts the performance of FANET is link outages. Due to shifts in UAV schedules and movements of FANET nodes, the quality of links declines quickly, leading to failures and updates in the topology. To address these challenges, routing protocols with advanced features are necessary for enhancing FANET systems.

3.3. Efficient Sensors Deployment

A system has been proposed in which a UAV network is utilized to collect data from users within a specific region. The purpose of this system is to monitor devices and smart home systems.

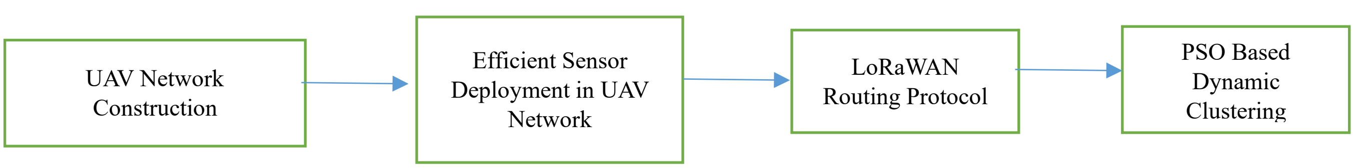

Fig. 1 ESRD-PDCA network model

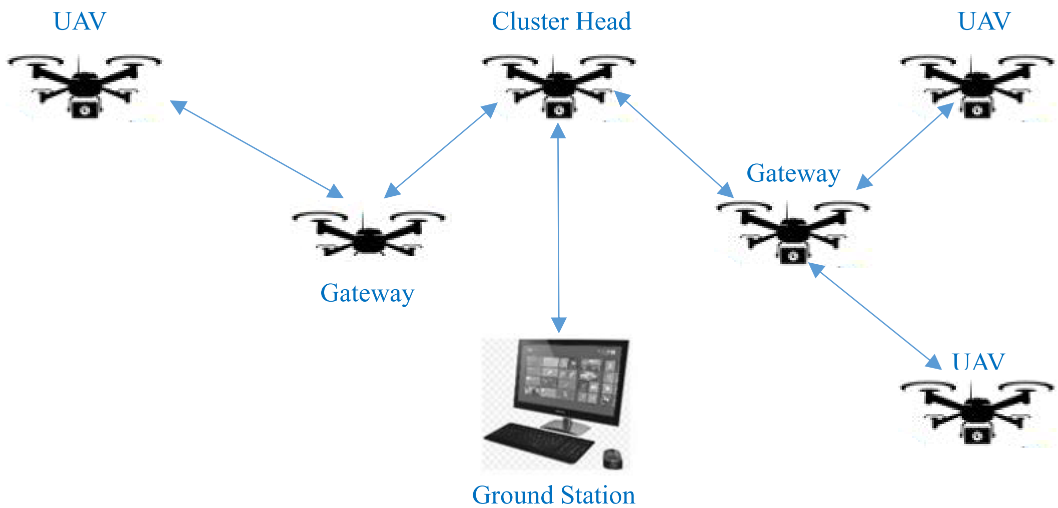

Fig. 2 The general architecture of FANETs

Users are able to interact with the UAV at different designated time intervals. The system consists of N users and L time slots. It is assumed that all users on the ground and the UAV have only one antenna each. In the uplink transmission, the n^{th} user utilizes a designated power P_n to transmit the signal x_n to the UAV. However, there are certain restrictions on the transmit power of each user that must be adhered to.

$$P_n \leq P_n^{thr}, \forall n \tag{1}$$

The maximum transmission power for the n^{th} user is denoted as P_n^{thr}. It is assumed that the L>=N; then, this means that each time slot can only be used by one user, and a user may use multiple time slots. As a result, there is no interference between users during uplink transmission. The signal received by the UAV during the l^{th} time slot can be represented as:

$$y[l] = \sum_{l=1}^{L} \tau_n[l] h_n[l] \sqrt{P_n[l]}\ x_n + n[l] \tag{2}$$

The signal sent by the n^{th} user is denoted as X_n. In this context, n indicates the presence of white Gaussian Noise (AWGN) at the l^{th} time slot with an average of zero. The integer variable is described as:

$$\tau_n[l] = \begin{cases} 1, \textit{if the } n-th \textit{ user occupies the } l-th \textit{ time slot,} \\ 0, \ \textit{otherwise} \end{cases} \tag{3}$$

The transmission strength of the connection between the unmanned aerial vehicle and the n^{th} individual in the l^{th} time slot is expressed as:

$$h_n[l] = \sqrt{\frac{\rho_O}{H^2 + ||w[l] - L_n||^2}} \tag{4}$$

In this scenario, ρ_O represents the power gain of the reference channel when the distance is $d_0 = 1m$. The UAV's position at a certain time is displayed by $w[l] = [x[l], y[l]]^T$ which consists of its x and y coordinates. The altitude of the UAV remains constant at H meters. The n^{th} user's location is denoted by L_n. Therefore, the movement of the UAV must adhere to these limitations.

$$w[l] = w[L]$$

$$||w[l+1] - w[l]||^2 \leq \left(\frac{vT}{L}\right)^2, \forall l \tag{5}$$

Equation (5) states that the UAV will return to its initial position after each cycle of duration T. The maximum speed of the UAV is represented by v, and the term $\frac{vT}{L}$ in Equation (5) represents the farthest distance it can cover in each time slot. To simplify, proposed work use. $\tau_n = \left[\tau_n\left[1, \ldots \tau_n[L]\right]\right]$, $\Theta = \tau_n = [\tau_1, \ldots . \tau_n]^T, p = [P_1, \ldots . P_N]$ and $W = [w[1], \ldots . w[L]]$ for convenient notation. The attainable data rate for the n^{th} user during the l^{th} time slot is given as:

$$R_n[l](p, \Theta, W) = B\log\left(1 + \frac{P_n[l] h_n[l]|^2}{\sigma^2}\right) \tag{6}$$

The typical speed at which the n^{th} individual is attended to by a UAV during the L time periods can be expressed as:

$$R_n(p, \Theta, W) = \frac{1}{L} \sum_{l=1}^{L} R_n\,[l] \tag{7}$$

The reason why the index $\frac{1}{L}$ is used is because each user is only assigned one time slot out of a total of 'L' time slots.

3.4. LoRaWAN Routing Protocol

A condensed version of the Destination-Sequenced Distance Vector (DSDV) routing protocol was chosen for implementation. Perkins and Bhagwat [7] proposed the concept of DSDV. Each node in this protocol maintains a routing table containing data about reachable destinations, related metrics, the path's next node, and other elements. In DSDV, routing advertisement messages contain both incremental packets and entire dumps that contain pertinent data. Full dumps are sent periodically and contain all routing table entries, while incremental packets only include changes since the last full dump. A key feature of DSDV is its loop-free routes 7. It required some adjustments to make it perform best on a LoRaWAN network, even though it was initially intended for mobile nodes. For example, as RNs are considered stationary, there is no need for a stability pointer in the routing table as in the original DSDV. Additionally, routes are deemed stable upon advertisement due to the expected stability of a LoRaWAN network. Lastly, unlike DSDV, there is synchronization between nodes set by a gateway.LNs create a LoRaWAN packet and add extra information for routing purposes before sending it through multiple hops. When the packet reaches a gateway neighbour, the additional information is removed, and only the LoRaWAN section is transmitted. This process can be seen in the second set of arrows originating from LN1 in Figure 3. The Application Server will receive the packet as if it was sent directly from the initial node, and its encryption remains secure throughout as part of a single-hop network within LoRaWAN. A routing database that includes a list of destinations, metrics to get to each one, the next pathway hops, destination sequence numbers, and time stamps to identify out-of-date entries is kept in storage by each registered nurse. As of this writing, the destinations are gateways, and the only gateway stored is the one with the fewest hops (metric).

Upon receipt of full updates, they are cross-checked against the current routing database, which gets updated in the event that new destinations or improved metrics for current sequence numbers become available. RNs can be separated into two categories: those with gateways as neighbours and those without gateways. Gateway neighbours have designated reception windows immediately after receiving a beacon where they change their channel parameters to match those the gateway uses when transmitting its beacon. Other RNs schedule their own updates after the expected time of the first full update in the next beacon cycle, after which they transmit their own updates. Packet Structure: Two sorts of packets are transmitted within the multi-hop extension: data packets containing application data and complete dumps, including routing information.Nodes create routes using full dumps, akin to distance-vector protocols in that each node only stores the next node in the path and its metric to a given destination. Sequence numbers from each destination are included to avoid loops. Figure 5 shows the layout of a complete dump packet.

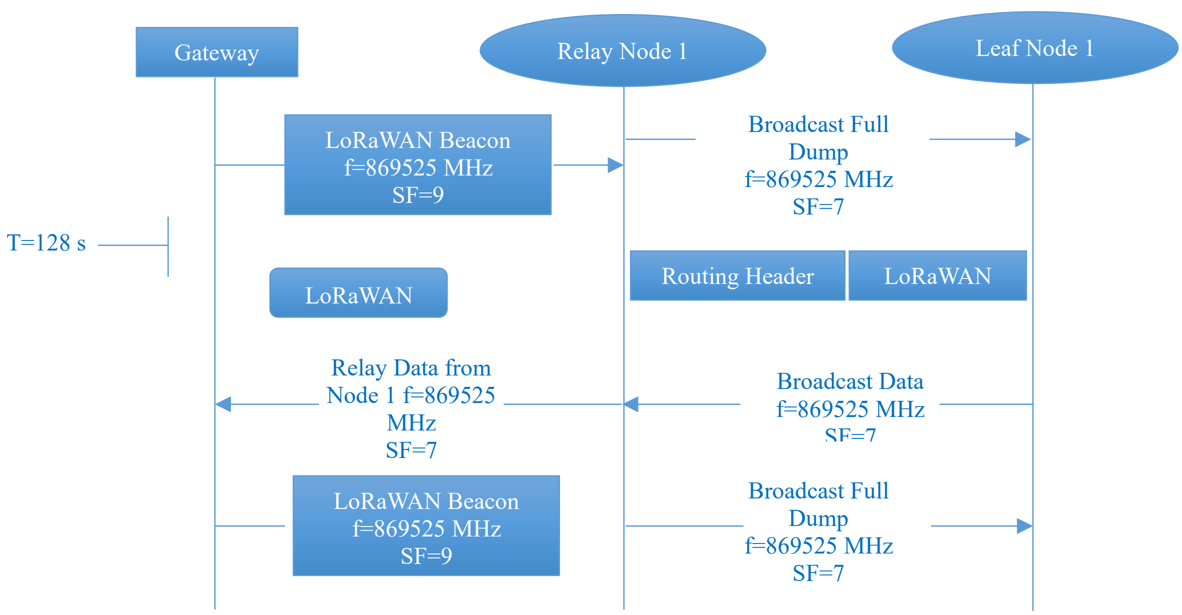

Fig. 3 Multi-hop solution timing

0	1	2	3		L
Type of packet	Source ID	Number of Routing Entries	Routing entries		
			ID	Metric	Sequence No
			0	1	2 4

Fig. 4 Packet structure of a complete dump, including field lengths in bytes and routing information

0	1	2	3	L
Type of packet	Unicast ID	Destination ID	LoRaWAN	

Fig. 5 Structure of an application data packet within the multi-hop network with field lengths in bytes

The Source ID field, which can only hold an ID from a neighboring node of the receiving node, identifies the sender.

The Source ID field is added as the subsequent hop for getting to the destination whenever a new destination is added to the receiving node's routing table. To enable the receiving node to appropriately interpret the entries, the number of entries is supplied. The ID, metric, and sequence number created by each destination are contained in each entry.

A simplified form of the sender’s routing table is represented by the list of routing entries. The packet should be transmitted to the next hop node, identified by the Unicast ID field. This guarantees that when a packet reaches an RN, it will only follow one path to its destination. When an LN transmits a packet, this field is assigned the broadcast value. The ID of the gateway, which is normally 0, usually correlates to the destination ID.

The data payload and additional fields listed in the LoRaWAN specification1 are contained in the remaining section called LoRaWAN. Packet reception: Upon receiving a packet, it undergoes a verification process to determine its type based on the “Type of packet” field. An instance of this would be a beacon from a gateway that receives its sequence number from a LoRaWAN beacon packet.

A further option is a full dump, in which several advertised destinations are extracted by iterating over the packet (as illustrated in Figure 2). Finally, if the packet represents application data, the receiving RN’s ID and the Unicast ID are compared. The RN looks for the next node in the path if there is a match. The three bytes of overhead are eliminated if the subsequent hop turns out to be a gateway. However, if it is not a gateway, then the Unicast ID field is updated to reflect the next hop destination.

Full Dump: Complete dumps are sent out as soon as a beacon is received or the first full dump within a beacon period. Every entry from the scanned routing table is included in a full dump packet sent to nearby devices. The first thing the program does throughout this procedure is compare the installation time of the current entry with the current timer value to see if it has become outdated. A certain number of beacon periods are exceeded by the difference before the entry is deemed stale.

In these instances, the entry is appended to the current full dump packet before being deleted from the table, and the sequence number is incremented to signify an unreachable destination. In a full dump packet from the previous beacon period, this location was previously identified as unreachable if the sequence number is even. As a result, it is still in the routing table and has not yet been communicated, ready to be sent out during the upcoming beacon time. It is also appended to the packet in this instance, after which it is eliminated from the routing table.

Packet Transmission: Each communication begins by conducting a Carrier Activity Detection (CAD) assessment of the channel to identify a proper LoRa preamble [8]. In the event that no preamble is detected, it assumes the channel is available and proceeds with the transmission.

However, if a preface is detected, the transmitter will make an effort to prevent any collisions. In this case, the transmitter implements an exponential backoff approach when multiple preambles are identified in a row.

Design Decisions: The following is a list of the design decisions made during the progress phase.

- The frequency band in which registered nurses (RNs) transmit is from 868.0 to 868.6 MHz, with a maximum duty cycle of 1%. When the RNs are programmed, the frequency at which full dumps and application data messages are sent must be specified. An RN will transmit to a gateway using a random channel from the set of 868.1, 868.3, or 868.5 MHz if it is in close proximity to the gateway.
- The current proposal does not support downlink communication. Considering the duty cycle constraints on RNs, ensuring reliable delivery of downlink packets to LNs at specific times becomes challenging unless they are continuously receiving data.

Prototype Description:

- The RFM95 868Mhz module from HopeRF was utilized as the transceiver for both the Leaf Nodes (LNs) and Relay Nodes (RNs). While the RNs were attached to an STM32L432KC Nucleo board, the LNs were connected to an Arduino Pro Mini.
- Raspberry Pi 3 was attached to running a packet forwarder to the iC880A-SPI board, which was manufactured by IMST, to serve as the gateway. For time reference, a GPS was also installed. A 1/2λ dipole antenna with a 2 dBi gain was employed.
- The Things Network (TTN) was an open-source LoRaWAN network that depends on community sourcing to set up a Network Server. It has a built-in network server as well.
- The incorporated TTN’s Node-Red for the Application Server. Since the TTN dashboard lacks persistent data storage capabilities, we were able to store test data for analysis at a later time.

3.5. PSO-Based Dynamic Clustering Approach

3.5.1. Fundamentals

Clustering

Data clustering is an essential task in the realm of unsupervised datasets, where the dataset is divided into clusters based on similar characteristics. There are two main types of data clustering: hierarchical and partition methods.

The hierarchical approach involves merging or splitting clusters, with agglomeration algorithms focusing on merging clusters until only one remains. On the other hand, divisive algorithms divide a cluster until each only contains one data point.

Partition algorithms, on the other hand, divide the data set into clusters at a single level. Examples of partition clustering methods include K-means, fuzzy C-Means, DBSCAN, and EM. The number of clusters and their structures are the main focus areas in data clustering.

For the former problem, there are few methods available, whereas there are several clustering algorithms to address the latter. Even with the advent of numerous clustering techniques, they are unable to satisfy the demands of efficiency, simplicity, quality, and automation. Finding the ideal number of clusters within a big data collection can be difficult.

To tackle this problem, Chang et al. suggested DNNM-clustering, a genetic clustering approach that makes use of dynamic niching with niche migration. In order to automatically evolve the number of clusters, this method dynamically finds niches and migrates them at each generation using a similarity function to predict approximate density shapes.

In order to determine the cluster number, Cheung created a competitor penalized competitive learning algorithm that has produced encouraging results. By maximizing a weighted likelihood, the algorithm determines the parameters of a mixture model and discards unnecessary seed points, moving the initial seed centers to their actual locations within the data set. Bayesian-Kullback Ying-Yang suggested a unified technique that provides insight into solving the cluster number problem for both supervised and unsupervised learning tasks.

Furthermore, Jain offered further methods for choosing cluster numbers, while Swagatam Das and Ajith Abraham developed an Automatic Clustering employing a Differential Evolution (ACDE) approach by providing a novel chromosomal representation. However, Most of these methods may not be feasible due to the need for numerous iterations of clustering algorithms to obtain decent results, as well as the computationally costly nature of model-based methods like penalized likelihood estimation and cross-validation.

PSO

Particle Swarm Optimization (PSO) is a method of optimizing nonlinear functions using social behaviour, first introduced by Berhart and Kennedy in 1995. This approach is considered population-based, with the population referred to as a "swarm" made up of individuals known as particles. Each particle 'i' in the swarm stores the following information:

- Its recent position
- Its recent velocity
- The finest position it has achieved so far, known as its personal best
- The finest position originates among all particles, known as the global best

A particle modifies its trajectory in space with each iteration to progress toward both the global and personal bests. The particle uses the following equations to modify its position and velocity after calculating these values:

$$v_{i+1} = wXv_i + c_1XrandX(pBest_i - x_i) + c_2XrandX(gBest_i - x_i) \quad (8)$$

$$x_{i+1} = x_i + v_{i+1} \quad (9)$$

The disinterest coefficient, which causes the speed to decrease over time, is a random value between 0 and 1. c1 and c2 are the acceleration coefficients are also present. Usually, the minimal error threshold or the maximum number of PSO runs decides the terminating condition.

The final condition is variable, just like other parameters, and is contingent upon the particular optimization problem. PSO has demonstrated excellent results in solving optimization problems and has recently been utilized for data clustering.

3.5.2. PSO-DCA Model

In part, it will provide an explanation of the method for solving the issue of automated grouping of MRS tasks. The solution involves the utilization of Dynamic Distributed PSO (D2PSO) and allocation techniques. The D2PSO, or the Dynamic Distributed PSO algorithm, is a popular approach for solving UAV target searching problems.

However, it has two main drawbacks: it can get stuck on local optimal solutions, and it may have slow progress in certain situations. Two new parameters were incorporated based on previous research into the PSO to address these issues. These characteristics help determine when particles are not improving, thus, not contributing to determining the global optimal solution. They are named Local Optima Detector for global best and Local Optima Detector for personal best.

This suggests that these particles are saturated and require an outside force to increase their search capacity. This problem is addressed by the D2PSO method, which broadens the search space by guiding particles toward uncharted territory that might yield better answers. Furthermore, the global best could become stuck in a local optimum and lead other particles in the wrong direction if it hasn't improved after a set amount of iterations.

An external push is used to overcome this issue and lessen its effects by releasing the trapped particle from the local optima location. This method preserves the fast convergence of PSO while successfully avoiding stagnation and local optima issues. D2PSO functions similarly to regular PSO in most circumstances, but it offers further advantages when these problems occur.

The local optimum detector: A parameter that plays a crucial role in the optimization process. It is continuously updated based on the current conditions. If a particle becomes stuck in a local optimum during the optimization process, the LOD will be increased. This indicates that the personal best for that particular particle has either remained constant or failed to improve over several consecutive generations of g^{Best} and LOD $_{g}^{Best}$. Dynamic concept: Our task involves creating a dynamic, decentralized version of the PSO algorithm. This approach utilizes multiple agents and gains its dynamic nature from their ability to adjust their parameters using user-provided values $\left(S_P, S_g, \varepsilon\right), \varepsilon\epsilon[0,1]$.

Particles p^{Best} that do not show improvement beyond a predetermined threshold LOD $_{p}^{Best}=S_p$ will be reconfigured using Equation (10), while those that fall below the threshold LOD $_{g}^{Best}=Sg$ will be reconfigured using Equation (11). Where, r, i_i=random $(1, M)_r$, 'M' refers to the total number of individuals in a population, i_2=random(1, size(g^{Best_hist})), and g^{Best_hist} represents the past figures of g^{Best}.

$$pBest\_temp = pBest\_temp_{i_1} + \frac{i_1}{i_1+i_2} X(gBest\_hist_{i_2} - pBest) \quad (10)$$

$$gBest\_temp = \min\left(pBest\_temp_i, gBest\right) \quad (11)$$

Flow chart of the ESRD-PDCA: Automatic Clustering D2PSO - Diagram showing the ESRD-PDCA process: Automated Clustering using D2PSO Originally used to replicate social interactions, PSO has gained popularity as an effective optimization technique. In the field of data mining, particularly in data clustering, PSO has been extensively utilized. This research expands on the PSO algorithm to address automatic clustering challenges.

The flowchart in Figure 6 outlines the comprehensive algorithm proposed in this study, which incorporates ESRD-PDCA to solve the MRTA problem. First, the number of task locations (NT), the number of UAV (NR), and the PSO parameters need to be specified. This model must also generate the first particles and initialize the LOD values. In this approach, a job grouping into clusters is represented by a particle.

Next, the phase uses a selected fitness function (either DB or CS) to calculate the cost value for each particle to evaluate the clustering. Then, it determines the personal best parameter for all particles and checks if it remains unchanged for a certain number of consecutive iterations. If this threshold is met, this model restructures the personal best value using Equation (12).

Afterwards, the global best parameter was calculated and compared to the historical values from previous iterations before updating the position and velocity of each particle. If there is no change in value for a given threshold, Equation (13) was used to calculate a new value. Otherwise, move on to the next step in the algorithm. After updating the positions and velocities of the particles, the procedure is repeated a predetermined number of times.

Lastly, the total number of clusters (KT), together with the locations of each cluster's centroid, were generated. The UAV task cluster assignment is handled as an MTSP problem, with the final distribution returned. After updating the positions and velocities of the particles, the procedure is repeated a predetermined number of times. Lastly, the system gives back the total number of clusters (KT) together with the locations of each cluster's centroid. The UAV task cluster assignment is handled as an MTSP problem, with the final distribution returned.

Objective function: This approach aims to reduce similarity within clusters and increase dissimilarity between clusters, which has been a focus in recent research. Multiple methods have been suggested for evaluating clusters, including the DB index, which minimizes average similarity, and the PBM index, which seeks to identify well-separated clusters with a small number of members, CS and VI. These measures essentially represent the ratio between the two objectives of clustering.

DB-index - Davies Bouldin invented the DB-index. It calculates the correlation between the distance between clusters and the overall distance inside a cluster. The intra-cluster distance is divided by the inter-cluster distance to get this value. One can ascertain the quantity of clusters by computing the mean separation between each object and their respective c_k, $S_n(c_k,c_{k'})$ cluster centers. The distance between the centers of clusters also plays a role in this calculation. Therefore, if the clusters are tightly packed and located far apart from each other, the resulting ratio will be small. As a result, a good clustering will have a low Davies-Bouldin index.

$$DB = \frac{1}{k}\sum_{k=1}^{k} max_{k\neq k'} \frac{S_n(c_k)+S_n(c_{k'})}{S_n(c_k, c_{k'})} \quad (12)$$

The CS-index, is a merging of both cluster diameters and the minimum distance between cluster centers. The calculation for this index is as follows:

$$CS = \frac{\frac{1}{k}\sum_{k=1}^{K}\frac{1}{|C_K|}\sum_{x_i}\in C_K \max x_i \in C_K\, d(x_i,x_j)}{\frac{1}{k}\sum_{k=1}^{K} min_{k\neq k'}\, d(c_k, c_{k'})} \quad (13)$$

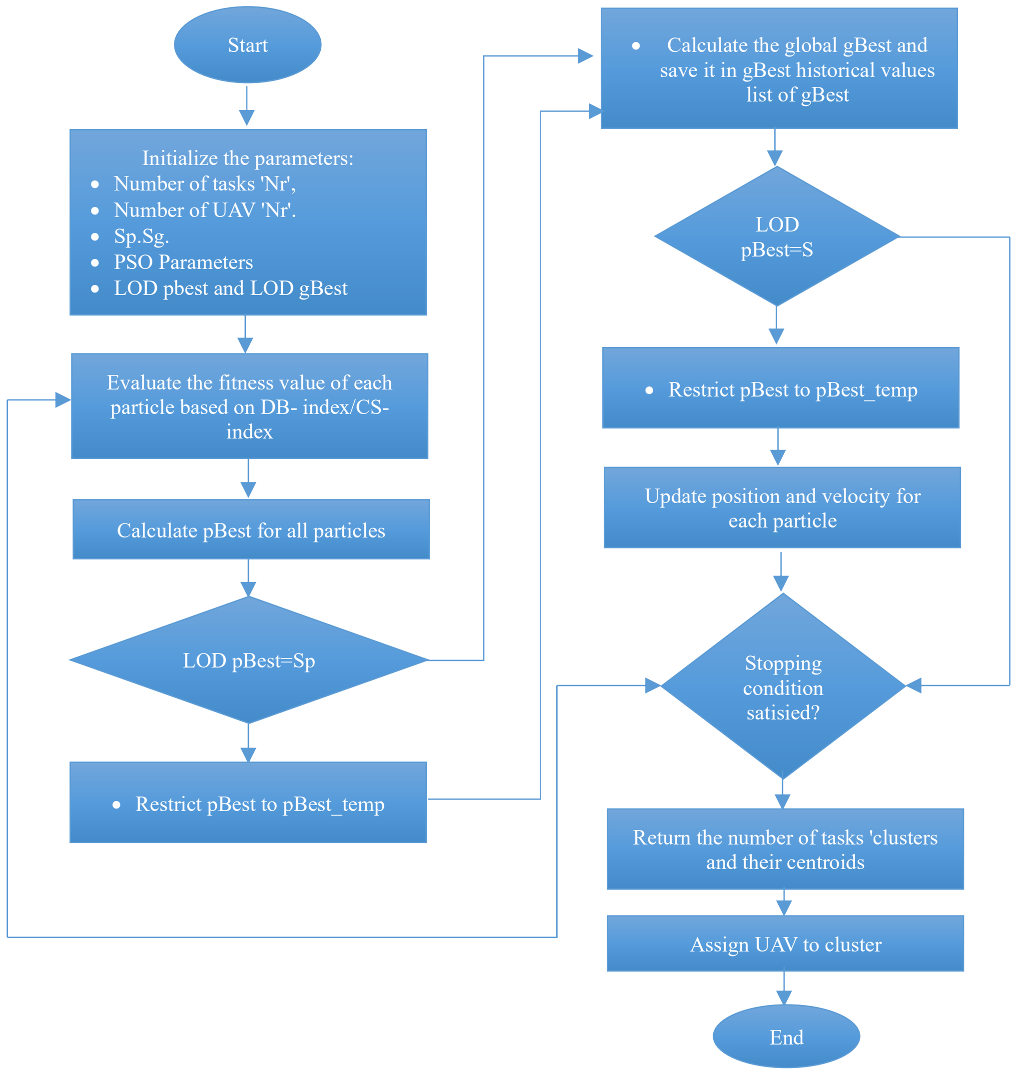

Fig. 6 Flow chart of clustering and assignment

What is the distance calculation formula? What is the number of elements in each cluster and the number of clusters overall? When comparing clusters of different densities or sizes, the CS index is helpful as it calculates the ratio between within-cluster scatter and between-cluster separation. Strong clustering is indicated by a low value. As demonstrated by Xu's research, the CS validity index is frequently used as a fitness function in evolutionary computational clustering techniques. Because of this, it is also employed in experiments as a fitness function.

4. Result and Analysis

4.1. Network Formation of UAV Model

The implementation of the proposed ESRD-PDCA is constructed in the software NS2, and the existing systems used for comparative analysis are ESSDS [26], DSSRCA [27], and EEUCH [28]. The parameters that are used for the performance analysis are Communication Delay (ms), Energy Efficiency (%), Data Success Rate (%), Network Throughput (Kbps) and Routing Overhead (Packets). The UAV network model in the NS2 software is illustrated in Figure 7. The proposed ESRD-PDCA algorithm is implemented in NS2. The simulation settings are shown in Table 1.

Table 1. Simulation Settings

Number of Nodes	10,20,30,40,50,60,70,80,90,100
Topology size	150 m * 150 m
MAC protocol	LoRaWAN
Source of Traffic	CBR
Traffic Flows	6
Traffic Rate	50 KB/s
Input Energy	25 Joules
Transmitting power	0.8 Watts
Receiving power	0.3 Watts
Speed of UAV	20-60 m/s

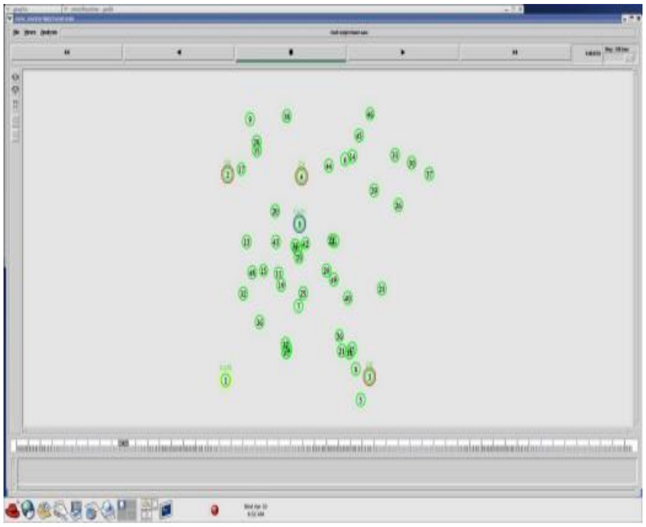

Fig. 7 UAV network model in NS2

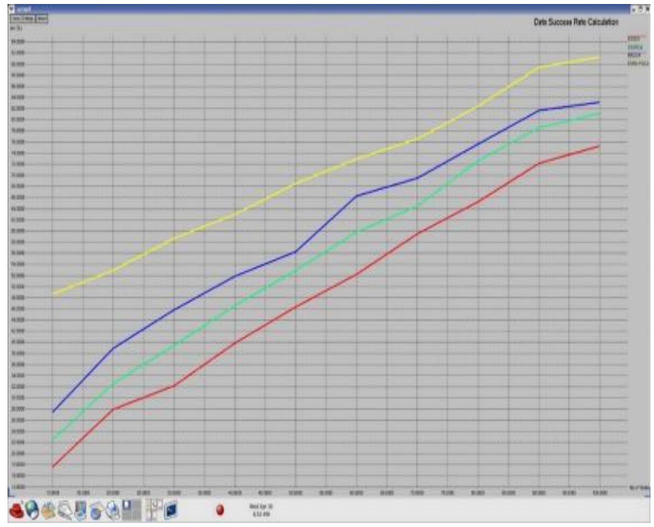

Fig. 10 Data Success Rate Calculation

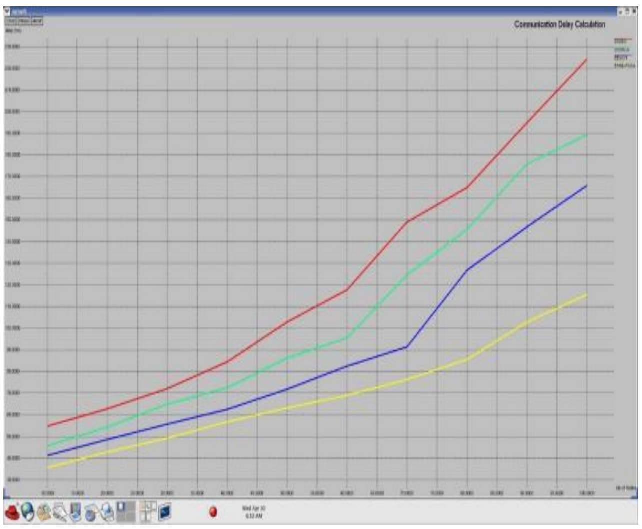

Fig. 8 Communication Delay Calculation

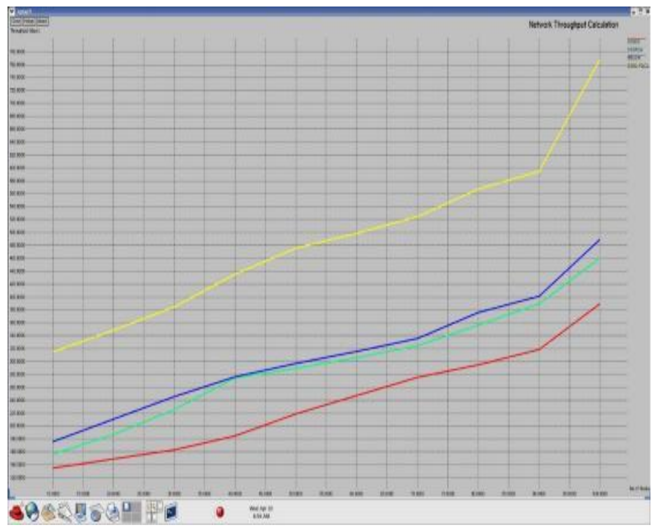

Fig. 11 Network Throughput Calculation

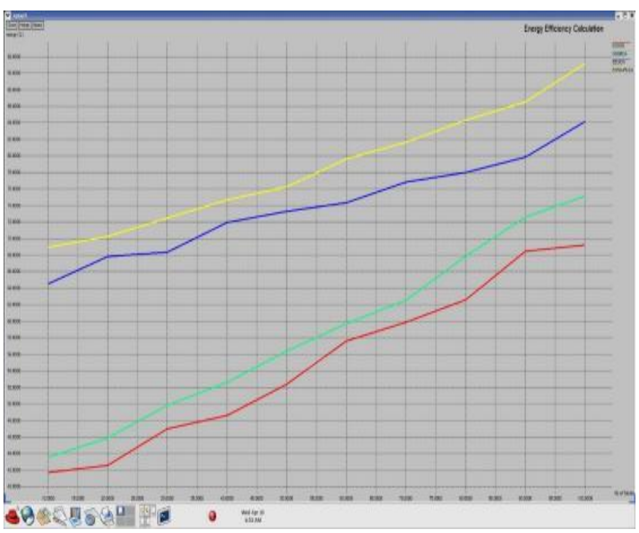

Fig. 9 Energy Efficiency Calculation

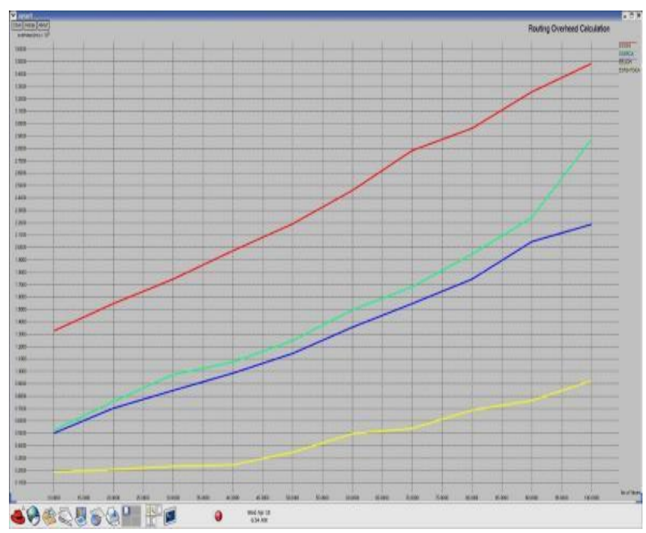

Fig. 12 Routing Overhead Calculation

4.1.1. Communication Delay Calculation

In the UAV network model, the communication delay is defined as the time required to transmit a packet of data over the communication link from one place to another. It is essential to reduce communication delays to achieve better performance. Figure 8 shows the communication delay calculation using methods like ESSDS, DSSRCA, EEUCH and ESRD-PDCA. From the figure, it is proven that the proposed ESRD-PDCA attained minimum communication delay when compared with the other baseline methods.

4.1.2. Energy Efficiency Calculation:

In the UAV network model, energy efficiency is defined as the energy that remains at the end of the simulation. It is essential to reduce energy consumption to achieve maximum energy efficiency among the nodes in the network. In Figure 9, the energy efficiency calculation is performed using methods like ESSDS, DSSRCA, EEUCH, and ESRD-PDCA. From the figure it is proven that the proposed ESRD-PDCA attained maximum energy efficiency when compared with the other baseline methods.

4.1.3. Data Success Rate Calculation

In the UAV network model, the data success rate is defined as the number of packets successfully delivered to their destination. It is essential to attain maximum data success rate to achieve high performance among the nodes. In Figure 10, the data success rate calculation is shown with the methods like ESSDS, DSSRCA, EEUCH and ESRD-PDCA. From the figure, it is proven that the proposed ESRD-PDCA attained the maximum data success rate compared with the other baseline methods.

4.1.4. Network Throughput Calculation

In the UAV network model, the throughput is defined as the total amount of data packets that get transmitted in a given time period. It is very essential to attain maximum throughput to achieve high performance among the nodes. In Figure 11, the throughput calculation is shown using methods like ESSDS, DSSRCA, EEUCH and ESRD-PDCA. The figure proves that the proposed ESRD-PDCA attained maximum throughput when compared with the other baseline methods.

4.1.5. Routing Overhead Calculation

In the UAV network model, the routing overhead is defined as the control messages and forwarded data packets, measured between the UAVs, Cluster Heads and the other nodes. Reducing the count of routing overhead is essential to achieve high performance. Figure 12 shows the routing overhead calculation using methods like ESSDS, DSSRCA, EEUCH and ESRD-PDCA. The figure proves that the proposed ESRD-PDCA attained minimum routing overhead when compared with the other baseline methods.

Table 2. Results analysis

Performance Metrics	ESSDS	DSSRCA	EEUCH	ESRD-PDCA
Communication Delay (ms)	224.25ms	189.24ms	165.85ms	115.46ms
Energy Efficiency (%)	69.25%	75.16%	84.17%	91.19%
Data Success Rate (%)	75.25 %	81.17%	83.12%	91.28%
Network Throughput (Kbps)	389.29 kbps	459.78 kbps	489.28 kbps	768.17 kbps
Routing Overhead (Packets)	3487packets	2872packets	2187packets	923packets

Table 2 shows the performance analysis of the proposed model and the existing methods.

5. Conclusion

This research aims to provide a maximum data success rate among the UAV network. For that purpose, the PSO optimization-based dynamic clustering approach is used, which helps to achieve efficient sensor deployment and reliable data collection in UAVs. The parameters that are calculated for the performance analysis of the proposed approach are Communication Delay, Energy Efficiency, Data Success Rate, Network Throughput, and Routing Overhead. At the end of the experimental analysis, it was proven that the proposed ESRD-PDCA performed better when compared with the earlier methods like ESSDS, DSSRCA, and EEUCH. In the future, load balancing and enhanced clustering models will be concentrated to improve the network's performance in densely populated areas.

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