Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Collision Free Scheduling with Consistent Data Collection using SOA based LDPC Approach in UAV Assisted LoRaWAN

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Abstract:
In UAV-assisted Internet of Things (IoT) applications, reliable and consistent functioning is an essential need. Specifically, using unmanned aerial vehicles (UAVs) and IoT deployed surfaces to assist in error-free data collection and collision-free transmissions in challenging areas seems to be an increasingly prevalent approach. Accurate data ensures reliability in decision-making, while consistent data optimizes network performance. Mainly to improve collision-free transmissions and data collection consistency, in this article, collision-free and consistent data collection using SOA based LDPC approach (CFCDC-SLA) is developed in the UAV-assisted LoRaWAN based network. The proposed method operated in two distinct operational phases. Firstly, the Seagull optimization algorithm was applied as the collision free scheduling algorithm. Secondly, we applied a low-density parity-check (LDPC) scheme to ensure consistent data collection, error detection, and data correction. The NS2 software is used to build the proposed UAV aided LoRaWAN implementation. 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.
Keywords: LoRaWAN,Collision free scheduling, Error Detection and Correction, Seagull Optimization Algorithm and Low-Density Parity-Check(LDPC).

1. Introduction

In recent years, UAVs have exploded in popularity among scientists and researchers thanks to their many useful features. In most cases, the kind, weight, range, application, endurance, etc. of a UAV determine its classification. Numerous uses call for specific varieties of unmanned aerial vehicles (UAVs)[1]. There are two main types of unmanned aerial vehicles (UAVs): those with fixed wings for long-duration surveillance and those with rotor wings for shorter-duration observation. A rotary-wing UAV's hovering capabilities and the fact that it can take off and land without a runway are two of its main advantages. Multiple subtypes of rotary-winged UAVs exist, including bicopters, hexacopters, octocopters, quadrotor tricopters, etc. The benefits and drawbacks of each platform are unique.

Unmanned aerial vehicles (UAVs) are ubiquitous aerial aircraft that offer crucial connectivity and concordance coverage in an efficient, low-complex manner[2]. A network of independent, interconnected UAVs has transformed both military and commercial aviation and opened the door for previously unheard-of advancements in infrastructure-less networking.

LoRaWAN can handle mobile nodes without requiring handovers between gateways, which makes it appropriate for IoT applications that are focused on asset tracking[24].UAV data gathering is the process of using drones that have sensors and cameras installed to collect data from the air. The effectiveness of UAV assisted data gathering will be significantly impacted by the placement and arrangement of sensors as well as the choice of data collection mode.

People sometimes equate UAVs with mobile connected devices; however, UAVs necessitate additional features and advanced planning for network groups, including transmission scheduling, data dissemination, direction and acceleration planning, and meeting Quality of Service (QoS) demands[3]. Through simulations, real-time research, and industry modeling, it is widely known and demonstrated that aerial and ground networks can collaborate to execute complicated tasks, overcoming obstacles of energy, environment, location, and trajectory. This paper centers on the dissemination of data through multi-UAV ad hoc networks. We describe aspects of data dissemination that pertain to both transmission scheduling and aerial mobility. First provided is an effective data distribution plan for multi-UAV assisted IOT.

However, a great number of collisions may occur given the existing LoRaWAN MAC layer communication strategy[24]. We suggest a collision-free scheduling approach to address this issue and permit transmissions at specific timeslots.

In UAV-assisted IoT networks, data reliability and precision are critical. Reliable information guarantees the network's optimal performance, and accurate data is essential for making trustworthy decisions. Techniques for error detection and repair are used to guarantee consistent data collecting.

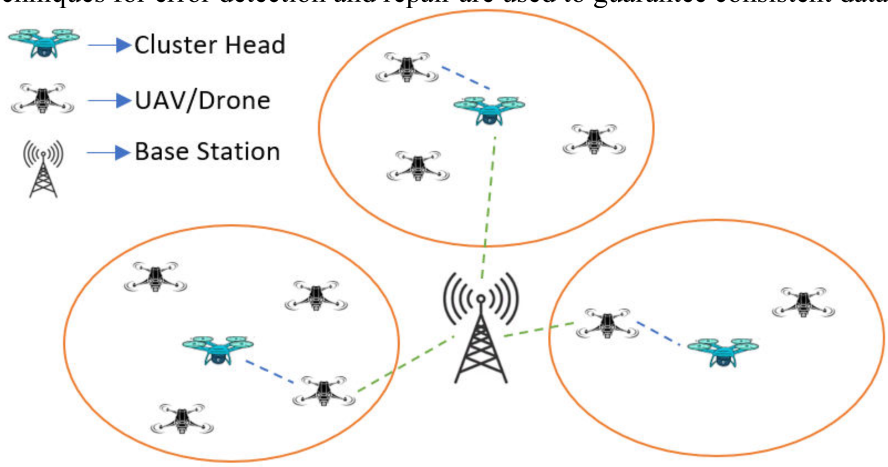

Figure 1- Network Model of UAV assisted IOT

Custer has been formed based on optimization algorithm, and based on cluster policy, cluster head (CH) and cluster Agent (UAV/Drone) were categorized. Normally, CH will be a decision-making process like choosing the optimal path, making a making a decision on transmission, which UAV has to communicate on time, etc. Based on the CH direction, the other UAV/Drone present in the cluster will function. Overall, the cluster will be communicated through Base station, which act as a transceiver. The network model of UAV assisted IOT is represented in Figure 1. In each cluster, the cluster members (UAV) send their collected data to the cluster head (CH), who aggregates the data. The CHs indicate the possible data collection points for the UAV. From the takeoff-point, the UAV visits each data collection point and communicates only with the CHs to complete the data gathering process. The blue dotted line denotes the initial trajectory of the UAV.

We continuously observe the topology and adjust it as needed. We also suggest an efficient and successful sleep timer and a back-off counter in light of energy depletion. Two UAV mobility and trajectory frameworks are described for improved coverage and data dissemination in multi-UAV ad hoc networks, building upon the transmission scheduling framework.

UAV support Vehicular ad hoc network architecture supports U2V/V2U communication, which finds application in various contexts, particularly in post-disaster operations[27,28,29]. These UAVs can operate remotely without an operator or hover silently in the air. By assembling a number of tiny UAVs and connecting them in an ad hoc manner, researchers created an expanding topic of study known as UAV ad-hoc networks. High mobility and frequent topological fluctuations characterize these types of networks, which create networking issues.

In this paper, we propose CFCDC-SLA, an optimization-based clustering and routing technique for UAV-assisted IOT that extends network lifetime. The CFCDC-SLA is one of the metaheuristic algorithms that mimic seagulls' natural behaviour.

The major contribution of this research is as follows:
1. A cluster head (CH) with an effective fitness function based on CFCDC-SLA is created. The primary reason for choosing this particular seagull optimization algorithm (SOA) is its inherent collision avoidance capability, which makes it useful for creating collision-aware data transfers in networks.
2. A routing method based on CFCDC-SLA is created using IoT networks aided by UAVs must prioritize data consistency and accuracy.
3. The superiority over other current techniques is illustrated through an analysis of a simulation of the CFCDC-SLA.

The remaining portions of this paper are arranged as follows:The prior study on collision-free transmissions and consistency data collection without error approach in UAVs is provided in Section 2. Section 3 provides the proposed algorithm. In Section 4, we discuss our proposed work simulation results and analysis, along with a comparison with the current routing protocols. The conclusion and recommended subsequent paths are provided in Section 5.

2. Exiting System

One of the challenges faced by UAVs during flight missions is Collision Free Scheduling and Consistent Data Collection [11]. The key to addressing this is collision free scheduling algorithm to allow transmissions at selective slots.Accurate data is crucial formaking reliable decisions and Consistent data ensures optimal performance of the network.

In [1], the authors S Parween and SZ Hussain.,recommended a work that implements suitable collision control and efficiently distributes resources in the LoRaWAN network using TCP. A method called Mini Batch K Means Clustering (MBKMC) multi-hop clusters LoRaWAN nodes and gateways to lessen the strain of computational complexity and network imbalance. The Osprey Optimization Algorithm (OOA) technique detect and prevent collisions.

In [2], the authors Canello G et. al.,contributed to a study that included: (i) the conception and field evaluation of a mobile LoRaWAN GW prototype built on packet sniffers, enabling the collection of information from LoRaWAN networks, that include those which have already been deployed; (ii) the preliminary performance evaluation of the system, exposing some intriguing trends, setting objectives for additional research, and identifying lessons to be learned over the experimental campaign. According to our empirical results, the optimal moving route for both the average energy required per collected packet and the number of packets collected is the Travelling Salesman Problem (TSP) scenario.

In [3], the authors Chia-an Hsu et. al., proposed two unique hashing-based techniques to accomplish data transmissions without collisions for receiver-initiated data collection. The author begins with an examination of a straightforward situation in which a data collector covers every device within a region of interest. The author then suggests a plan that enables each device to upload data at a predetermined time. Next, we expand our plan to accommodate a more practical situation in which Internet of Things devices are dispersed throughout a wider area that is too big for a single data collector to cover.

In [4], the authors, Hengshuo Liang et. al., accessed the problem space into a three-dimensional model that takes the approach, task, and resource into account. The authors present an innovative approach based on the identified issue space that uses an unmanned aerial vehicle (UAV) as a vital component of the forthcoming mobile network in order to accomplish sporadic connections between IoT devices and permit data gathering using the delay tolerant network (DTN) protocol. A technique for path planning based on the Hilbert Curve is used to determine the UAV flight path. Through a series of quantitative studies, the authors confirm the advantages of our technique over other baseline alternatives and test its effectiveness in a network emulation environment.

In [5], the authors Hexian Kuang et. al., proposed a multi-event data collection architecture for smart agriculture using unmanned aerial vehicles and the internet of things that is time-limited. The authors first illustrate the construction of the agricultural IoT framework, utilizing UAV assistance for data collection. Secondly, they show how the system functions and processes based on the event priority. Finally, they provide a flight path planning approach based on the event's priority.

In [6], the authors Shihab Jimaa et. al., recommended the implementation of the collision aware transmission priority scheduling (CA-PST) deep learning-based technique to reduce the high rate of packet collisions in extremely crowded wireless networks. The proposed CA-PST is used on the lowrange wide area network (LoRaWAN) architecture. The LoRa gateway sets the nodes to certain transmission protocol classes based on the expected number of packet collisions. Unsupervised learning clustering assists in allowing nodes at higher transmission priority clusters to communicate with the gateway using class C, thereby preventing packet collisions.

The authors of [7], Dimitrios Zorbas and Brendan O'Flynn et al., have proposed a successful and energy-efficient method that makes use of drones as mobile gateways that routinely fly over the network to collect data. The author considers both a point-to-point LoRaWAN communication protocol and a node-to-drone communication model.

The objective of [8] the authors, Natalia Chinchilla-Romero et al., introduced the Collision Avoidance Resource Allocation (CARA) algorithm that control collusion into resource provisionsystem. CARA uses the orthogonality of spreading factors and the multichannel nature of LoRaWAN networks to prevent device collisions.

In [9], the author Guillaume Ferre.,proposedon examine packet loss and collisions when taking LoRaWAN into account. We derive closed-form formulas for the probability of collision and packet loss based on the LoRaWAN features. Simulation findings confirm our theoretical developments. They also demonstrate that their theoretical equations for the collisions characterize them more accurately than the Poisson distributed process.

Dimitrios Zorbas, Brendan O'Flynn, et al. presented a collision-free time-slotted scheduling approach in [10]. Every node unconventionallychooses when to carry a packet built on its exclusiveuniqueness, which is then modulo-operated to generate a slot number. Real-world trials and simulations indicate that this system can achieve very high dependability when the nodes synchronize. It also only requires the broadcast packet from the gateway, with no additional communication overhead.

The authors Anna Triantafyllou et al. [11] created a new Medium Access Control (MAC) protocol named FCA-LoRa with the aim of enhancing collision evasion in LoRa wide-area networks through the use of fairness. The network gateway transmits beacon frames, laying the groundwork for the unique scheduling method that establishes connections with end devices.

In [12], the authors Martin Heusseet. al., proposed an improved packet delivery ratio (PDR) model that outperforms the models found in the literature in two ways: firstly, it considers the sum of disruption authorities when multiple colliding frames occur, even if the interference preexists; and secondly, it examines the dependency between overcoming ambient noise and dominating colliding frames. Additionally, the framework includes the scenario of a gateway with multiple receivers.

In [13], the authors HyunbumKimet. al.,presented a framework for building a UAV augmented boundary that is collision-free and ensures detection of several forms of intruder infiltration. Formally, they formulate a problem that aims to reduce the overall movement distance of UAVs, enabling the construction of a reinforced barrier that is collision-free, starting from the UAVs' initial positions. To tackle the challenge, researchers develop possible positions that can accommodate the UAVs' flexible motions. Next, they suggest a novel zone-based strategy.

In [14], the authors Ziji Shi and Wee Keong Ng.,developed an A* algorithm-based collision-free path planning algorithm. The primary innovation is the creation of a heuristic function that takes waiting time into account. Researchers further demonstrate that the suggested approach is optimal, with an additional waiting penalty because the heuristic is admissible.

In [15], the authors Elmokadem T and Savkin, A.V.,specifically designed to facilitate secure independent activities in dynamic, partially-known, three-dimensional (3D) settings. In order to offer fast, reflex-like responses to recently discovered impediments, this system cartels a global trackpreparation algorithm called RRT-Connect, with a responsivegovernor rule based on sliding mode control.

In [16], the authors Peiwang Zhang et. al.,approached a problem as a non-convex optimization problem and repeatedly tackled it using a sequential convex programming algorithm, which convexifies non-convex constraints. The author linearizes the UAV's dynamical equations and penalize collision-free constraints using a hinge loss.

In [17], the authors Aya Abdelhady and Ahmad Hosny Awad Eid.,suggested a simplified, static habitat with established borders and obstacles for UAVs to fly in, along with optimal 2D pathways and trajectories. They generate the trajectories for UAVs using quintic Pythagorean Hodograph curves, also known as PH curves, to ensure they are viable, smooth, and flyable. Two kinematic and dynamic limits on the UAV are curvature boundaries and minimal bending energy. The generated pathways meet both of these requirements.In [18], the authors Chao Dong et. al.,suggested two algorithms for UAV coursedevelopment in law-altitude airspace: the particle swarm optimization rapidly-exploring random trees (PSO-RRT) algorithm and the protected sub-airspaces planning (SSP) algorithm.

In [19], the authors Verma SC et. al.,discussed a useful navigation method for nonholonomic Unmanned Aerial Vehicles (UAVs) in environments with a lot of moving and immovable objects in 3D. Dynamic programming (DP) couples with a reactive control method to achieve the desired result. Utilizing the DP, the UAVs can maneuver over established immovable hurdles and obstructions.

In [20], the authors Kefan Wu et. al.,Addressed the issue of dispersed formation tracking in heterogeneous nonlinear multi-UAV networks by bearing measurements. Initially, to accomplish the intended formation, a unique bearing-only protocol is created for the following agents: In particular, the author takes bearing data to create a compensation function that addresses the non-linearity and actuator defects in the agent dynamics. Under specific time delays, the Lyapunov approach can guarantee the stability of the suggested strategy.

In [21], the authors XinglingShaoet. al.,proposed an approach for UAVs to approximate a cooperative target using model-guided reinforcement learning (RL) in a predetermined amount of time, ensuring collision-free behaviors and the achievement of reinforced tracking capability. First, we develop a polar frame-based fixed-time enclosing controller to force UAVs to reach the target circles within a predetermined timeframe. Moreover, we build the supplement component using the deep deterministic policy gradient (DDPG), which interprets disturbance rejection and collision avoidance limits as two skilled reward functions, thereby enhancing tracking performance and imparting collision avoidance skills.

In [22], the authors Aliasgar S. Malik et. al.,conducted a thorough analysis of the A* algorithm's use in UAV route planning. This inquiry aims to analyze A*'s performance in terms of path optimality and adaptability across a range of test cases. The publication provides a thorough description of the method, including its guiding ideas and heuristic search approach.

In [23], the authors Seo D and Kang J.,proposed a unique velocity-adaptive 3D local path planning method (3DLPP) for a single unmanned aerial vehicle (UAV) that operates in real-time obstacle collision avoidance (CA) while following an established itinerary. Localized path candidates are generated by applying cost functions in three-dimensional space during local path planning in order to eliminate obstacles in real time. Using a well-defined cost function that minimizes centripetal acceleration, the model predictive control law (MPC) is used to estimate velocity and acceleration profiles in real-time.

3. Proposed System

3.1 Proposed CFCDC-SLA Model

The proposed CFCDC-SLA system has been classified into seven step procedure to carry full set of operation. Basically, this CFCDC-SLA was classified into two working operation, based on Collision Free Scheduling and Consistent Data Collection. Figure 2 represents the Proposed CFCDC-SLA Model.

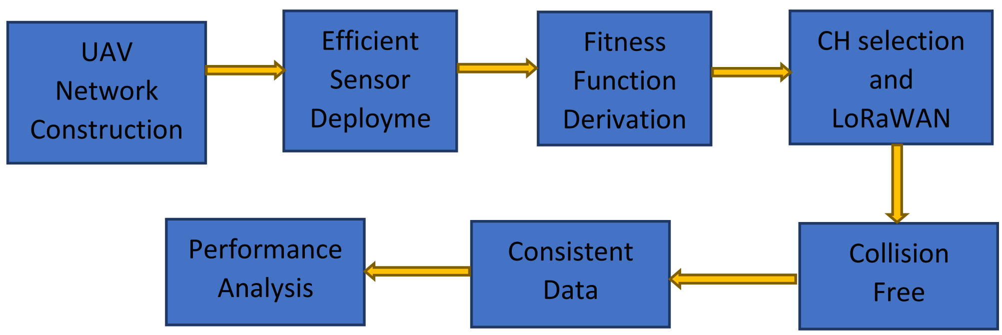

Figure 2- Proposed CFCDC-SLA Model

3.2Seagull Optimization Algorithm(SOA) based Dynamic Clustering Approach

Choosing the proper cluster head is of utmost significance for developing a more effective dynamic clustering strategy. This section employs the SOA to choose the cluster and routing leader. This section will elucidate numerous applications of SOA. Seagulls belong to the Laridae family, which spans a broad variety of parts of the biosphere. Even though there are many kinds of seabirds, seagulls are particularly appealing since they are tenacious and have a powerful desire to hunt their prey. As a result, seagulls are intelligent birds since they exhibit migrating and hunting behaviours. People prefer seagulls over other birds that live in both saltwater and freshwater environments due to their unique characteristics and ability to make snap decisions. We will discuss two significant activities, namely migration and attacking, in more detail in the following paragraphs.

3.2.1 Seagull Migration

During the process of migrating, the seagull is required to compensate for the potential outcomes of the following numerous scenarios.

a. *Preventing collisions:*

In order to prevent collisions between Seagull, additional limits have been imposed on the determination of the optimal location of the exploring agent, as shown in Equation (1).

$$ASA = SA \times Pl(x) \quad (1)$$

Whereas the drive attributes of the search agent are denoted by the letter ‘SA’, the current iteration is denoted by the letter ‘x’, the search agent's current location is denoted by the letter ‘Pl’, and the ‘ASA’ is not affected by the agents that are continuing to operate. It is possible to obtain the motion patterns for the search agent by using Equation (2).

$$SA = Fc - (x \times (Fc / n)) \quad (2)$$

Where x=0,1,2….n Iteration. And ‘n’ represents as maximum iteration. ‘Fc’ denotes Frequency Constraint, is starts as 2, since FA is denoted linearly and condensed from Fc to 0.

b. *Movement in the direction of optimal neighbours:*

Once neighbour collisions are eliminated, exploration agents are identified in the direction of optimal neighbour motions by equation (3).

$$Ms = RA \times (EA(x) - Pl(x)) \quad (3)$$

where ‘Pl(x)’ and ‘Ms’ denote the search agent and its position; ‘RA’ is designated as a random agent responsible for the effective evaluation between inspection and manipulation; ‘EA(x)’ denotes the exploration agent with maximum fitness; and Equation (4) expresses the random value computation.

$$RA = 2 \times S = SA^{2} \times RQ \quad (4)$$

We define 'RQ' as a diverse random quantity accessible within the range [0, 1].

c. *Remain close to the finest search agent:*

Finally, Equation (5) relatives the improved search agent's position to the optimal search agent.

$$dist = |ASA + BFA| \quad (5)$$

The distance between the Best-Fit Search Agent (BFA) and the Actual Search Agent (ASA) is represented by "dist".

3.2.2 The seagull invades its prey

The reduced computing requirements for the exploratory phase justify the implementation of this method. During the attacking phase, seagulls change their migrating conditions as they focus on maintaining their altitude in reaction to weight and air currents. The ability to rotate in mid-air allowed them to hit their target. Equations (6–9) can be used to characterize the performance of the twisting drive.

$$X = Rad \times \cos t \quad (6)$$

$$Y = Rad \times \sin t \quad (7)$$

$$Z = Rad \times t \quad (8)$$

$$Rad = U \times e^{tV} \quad (9)$$

where "e" is the actual logarithm base; "u" and "v" are the spiral shape quantities; "t" is designated as an indiscriminate amount by the range $[0 \leq t \leq 2\pi]$; and "Rad" is the spiral's extent on each chance. The search agent updates its advancement using Equation (10).

$$Pl(X) = (dist \times X \times Y \times Z) + OR\_Loc(X) \quad (10)$$

OR_Loc (X) marks the location of the remaining search agents as an optimal response.

3.3 LDPC Approach

LDPC[25,26] codes are a dynamic error correction coding technology that has acquired a lot of attention in the past 10 years because they can parallelize computations. This has allowed for the development of hardware codecs, typically for high-speed industrial communication standards, with extremely efficient algorithms and high throughput.

The parity check matrix (PCM) H, which details the precise parity checks involving the transmitted message bits, determines the particular LDPC code[25]. Sparseness, a crucial feature of PCM, allows low-complexity message delivery systems to iteratively decode LDPC codes. Low-complexity encoding methods are becoming more and more popular. Code architecture and execution are examples of nonbinary coding strategies.

Forward Error Correction (FEC) codes add extra parity bits before each transmission. LoRa uses Hamming codes, recognized for their significantly suboptimal error-correcting capability yet relatively easy to implement.

The term "coding gain" describes the degree to which FEC codes can reduce the signal-to-noise ratio (SNR) required for effective data retrieval.

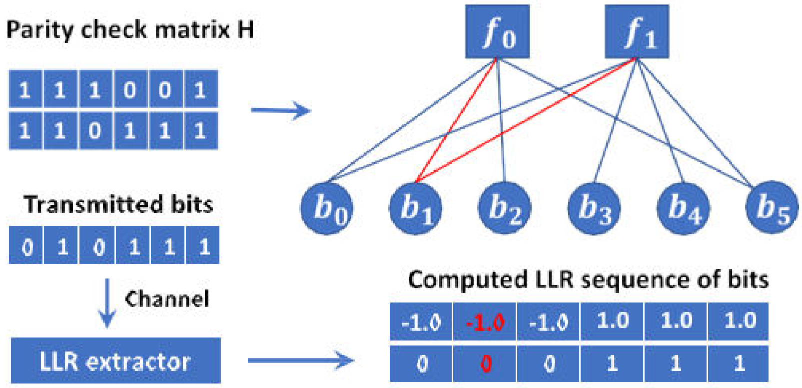

Figure 3parity-checkmatrixand itsassociated Tannergraph [25].

Figure 3 displays a graph where each row represents a check node (square) and each column represents a bit node (circle) in the equivalent graph on the right. An illustration of the calculated six-bit Log-Likelihood Ratio (LLR) using our LLR extractor is shown below.LDPC codes transform a data packet consisting of ‘K’ bits into a frame of ‘N’ bits by adding ‘M’ parity check bits to the original ‘K’ bits, where ‘M’ is equal to N- K[25].

Low-Density Parity-Check (LDPC) decoder[25,26]:Bit-flipping and SBP are the two primary LDPC decoding techniques. Bit-flipping is a hard-decision decoding method where the data is decoded using a binary bit stream as the input. Conversely, SBP functions as a decoding method that takes received bit dependability into account. To provide improved estimates, it takes LLR as input.

Thus, this paper mostly concentrates on SBP. Here is a summary of the SBP decoding algorithm:

Step0: Bit Nodes' first contact with Check Nodes. Demodulation enables the log-likelihood Ratio (LLR) of every bit to be obtained upon packet reception. Each bit node starts the decoding process by sending its Log-Likelihood Ratio (LLR) to the linked check nodes.

Step 1: involves upgrading messages sent from check nodes to bit nodes. A check node fi uses the following formula to determine the message it will send back to bit node "bj" after receiving messages from all of the bit nodes it is associated with:

$$\eta_{f_i \to b_j} = 2\tanh^{-1}\left(\prod_{b'_j \in N(f_i) \setminus b_j} \tanh\left(\frac{\lambda_{b'_j \to f_i}}{2}\right)\right) \quad (11)$$

Step 2: Upgrading information transmitted from Bit Nodes to Verify Nodes. After receiving information from all associated check nodes, node 'bj' constructs a notification, which it then delivers back to check node 'fi'.

$$\lambda_{b_j \to f_i} = \text{LLR}(b_j) + \sum_{f_i' \in M(b_j) \setminus f_i} \eta_{f_{i'} \to b_j} \quad (12)$$

Step 3: Validating the Closure Condition. Prior to transmitting the modified information to their respective associated check nodes, all bit nodes initially verify if their closure requirements have been satisfied. In order to accomplish this, each bit node 'bj' updates its Log-Likelihood Ratio (LLR) value 'λbj' based on the messages ηf `j→bj received from all of its associated check nodes. Let λbj represent the output of the Sum-Product Belief Propagation (SBP) method.

$$\lambda_{b_j} = \text{LLR}(b_j) + \sum_{f_i' \in M(b_j)} \eta_{f_i' \to b_j} \quad (13)$$

3.4Apply SOA and LDPC into Proposed Model

Step 1: We initially construct the UAV network.

Step 2: After that, the sensor nodes and the multi-tiered clustering model are developed. Next, we use the proposed SOA to determine the fitness function.

Step 4: Next, based on SOA, the CH selection process takes place, advancing the routing over IoT networks helped by UAVs.

Step 5: After the clustering and routing procedures, we examine the sent data to determine if it is collision-free.

Step 6: Once it is known that there are no collisions in the transmission, the LDPC method is used on LORAWAN[24] to make sure that data collection is always the same by finding and fixing errors.

3.5 Cluster Head selection in CFCDC-SLA

We applied the SOA for CH selection and routing. Since the suggested CFCDC-SLA includes a collision-avoidance characteristic by design, it is mostly useful for producing congestion-aware routing with reliable data collection. The proper fitness function can be determined to determine the correct fitness value. Several features, including network coverage, communication cost, residual energy, and node degree, were considered.

To find the network coverage, the below equation (14) was applied.

$$\text{Min f1} = \frac{1}{nT}\sum_{i=1}^{n} Nc(ni) \quad (14)$$

To find the communication/ transmission cost to the neighbour hub/host, the below equation (15) was described,

$$\text{Min f2} = \frac{1}{nT}\sum_{i=1}^{n} Np(ni) \quad (15)$$

To find the residual energy, which was represented as equation (16),

$$\text{Min f3} = \sum_{i=1}^{m} \frac{1}{E_i^{ch}} \quad (16)$$

To find the degree of the node/host, equation (17) was represented,

$$\text{Min f4} = \sum_{i=1}^{m} \text{Ii} \quad (17)$$

In equation (14,15), 'n' represents number of nodes. In equation (14,15,16,17) where applied into normalization process 'f(x)' and finally equation (18) were drawn to obtain minimum fitness value.

$$\text{Min fitness} = \alpha1\ f1 + \alpha2\ f2 + \alpha3\ f3 + \alpha4\ f4 \quad (18)$$

3.6 SOA based routing

During this phase, the SOA finds the best transmission path from the source node to the destination that avoids collisions.The following fitness metrics—queue length, link quality, communication cost, and residual energy—are used to optimize the routing path creation. There are several stages involved in this path creation process, including initialization, fitness function derivation, representation, and iterative procedure.

Equation (19) were applied to find the Queue Length for fitness function used in routing purpose,

$$Q = \frac{RP(n_k)}{Total} \quad (19)$$

In equation (19), 'Q' represents the Queue length and 'RP' represent received packet and 'total' as Total Buffer.

Equation (20) is used to represents Link Quality for fitness function used in routing purpose,

$$L = \frac{1}{frd\ X\ bck} \quad (20)$$

In equation (20), ‘L’ represents the Link Quality and ‘frd’ for forward data transmission and ‘bck’ for Backward data transmission. Based on all fitness features, single fitness function was derived as equation (21),

$$RF = \delta_1 \times Q + \delta_2 \times L + \delta_3 \times CC + \delta_4 \times RE \qquad (21)$$

Where, ‘RF’-> Routing Fitness, ‘Q’->Queue length, ‘L’-> Link Quality, ‘CC’-> Communication Cost, ‘δ’->weighted parameters and ‘RE’-> Residual Energy.

3.7 Working progress of Proposed Algorithm

Initially, the seagulls get acquainted with route data and are equipped with the x1 and y1 coordinates of the CHs that will host the following hop.We use the fitness metric in Equation (21) to identify the best overall population of seagulls.

To prevent collisions during the migration procedure, equation (21) is applied. Following the completion of the collision avoidance, the best population—that is, the optimal navigation path—is used to update the remaining communities.

In addition, the seagulls' locations are altered based on the stage of excavation. Using the most suitable solution from the CFCDC-SLA, the locations are updated in this phase.Lastly, the best transportation path from the source CH to the point of destination is provided by the established CFCDC-SLA.After it is established that there are no transmission collisions, the LDPC technique is applied on LORAWAN[24] to ensure that data gathering is consistent by identifying and resolving faults.

4.Result and Discussion

This part covers the results of the CFCDC-SLA algorithm, which was created as a collision-free scheduling technique to enable transmissions in UAV-based IoT using LORAWAN. The following section provides a comprehensive description of the findings and discussion of the suggested CFCDC-SLA approach. We implemented the CFCDC-SLA using the Network Simulator-2.34 (NS-2.34).The simulation settings are shown in Table 1.

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

Table 1 Simulation settings

a) Communication Delay:

Communication delay refers to the duration it takes for a message or signal to travel from its sender to its receiver. This encompasses delays in delivery, routing, processing, and queuing. Networks and distributed systems may encounter latency that impedes data transmission. In Fig. 4 Communication Delay of CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV is shown. Figure 4 shows that CFCDC-SLA outperformed CPP-WSO, ESRD-PDCA, and EEDP-UAV by 23.13%, 30.17% and 6.56% respectively.

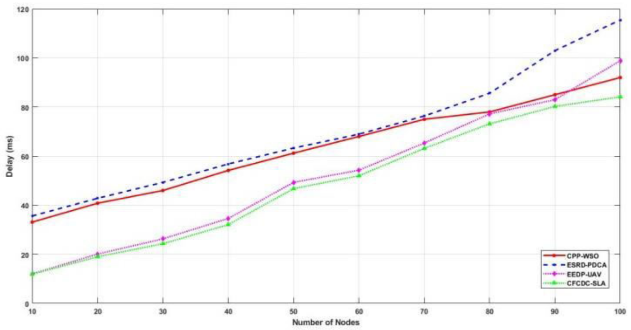

Figure 4: Effect of Node Density on Communication Delay in CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV Algorithms.

b) Energy Efficiency:

Energy efficiency entails using a smaller amount of energy to achieve the same output or result. This is the optimization of processes, equipment, and systems to reduce energy consumption while maintaining performance levels. In Fig. 5 Energy Efficiency of CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV is shown. Figure 5 shows that CFCDC-SLA outperformed CPP-WSO, ESRD-PDCA, and EEDP-UAV by 12%, 16.84% and 10.27% respectively.

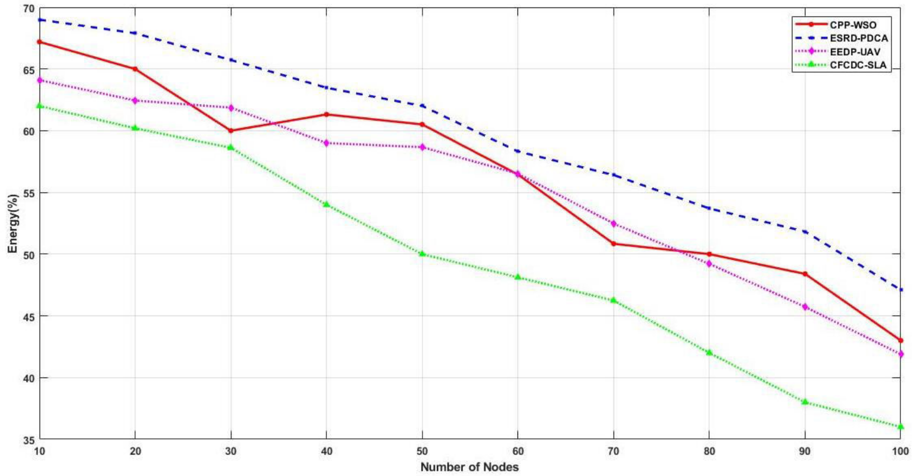

Figure 5: Effect of Node Density on Energy Efficiency in CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV Algorithms

c) Data Success Rate:

The percentage of accurately transmitted and received data packets within a communication network is known as the data success rate. It assesses the reliability and efficiency of data transfer while considering any errors or losses. In Fig. 6 Data Success Rate of CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV is shown. Figure 6 shows that CFCDC-SLA outperformed CPP-WSO, ESRD-PDCA, and EEDP-UAV by 2.96%, 0.60% and 1.29% respectively.

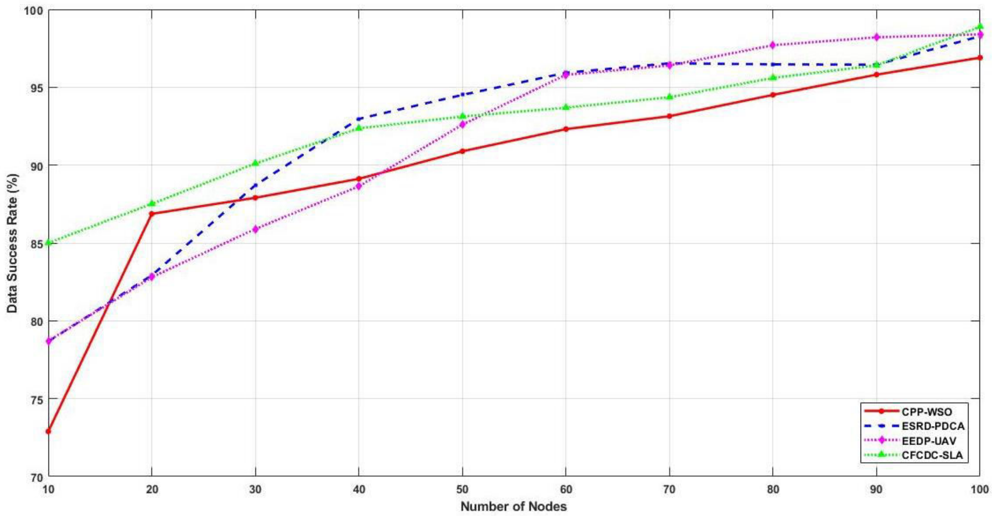

Figure 6: Effect of Node Density on Data Success Rate in CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV Algorithm

d) Network Throughput:

The metric known as throughput measures the speed at which data moves between various locations on a network. We typically quantify it in terms of bits per second or data packets per second. In Fig. 7 Network Throughput of CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV is shown. Figure 7 shows that CFCDC-SLA outperformed CPP-WSO, ESRD-PDCA, and EEDP-UAV by 2.95%, 2.73% and 0.52% respectively.

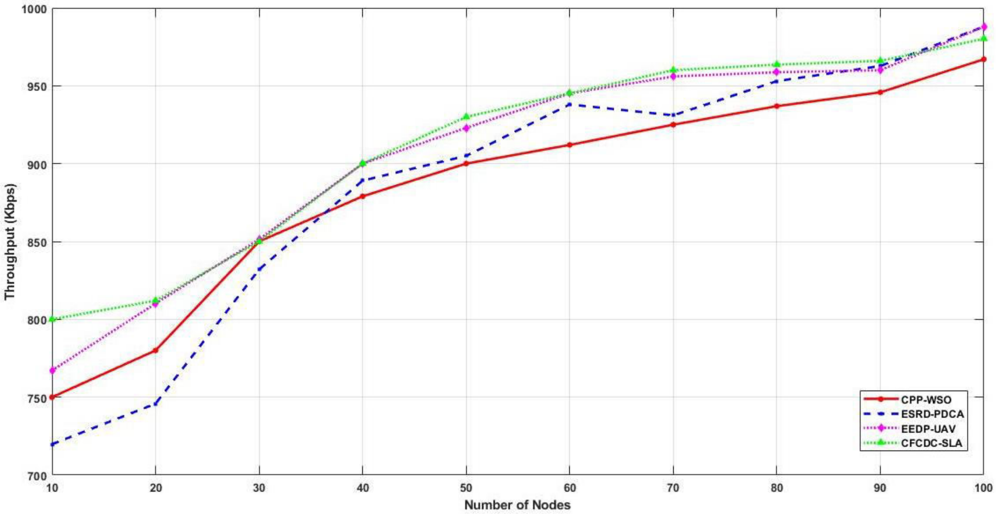

Figure 7: Effect of Node Density on Network Throughputin CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV Algorithm

e) Routing Overhead:

Routing redundancy is the additional network traffic that arises from the transfer of routing data between network nodes. The content includes control messages, updates, and additional protocol-specific data that is critical for maintaining precise routing tables. In Fig. 8 Routing Overhead of CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV is shown. Figure 8 shows that CFCDC-SLA outperformed CPP-WSO, ESRD-PDCA, and EEDP-UAV by 41.65%, 45.34% and 7.84% respectively.

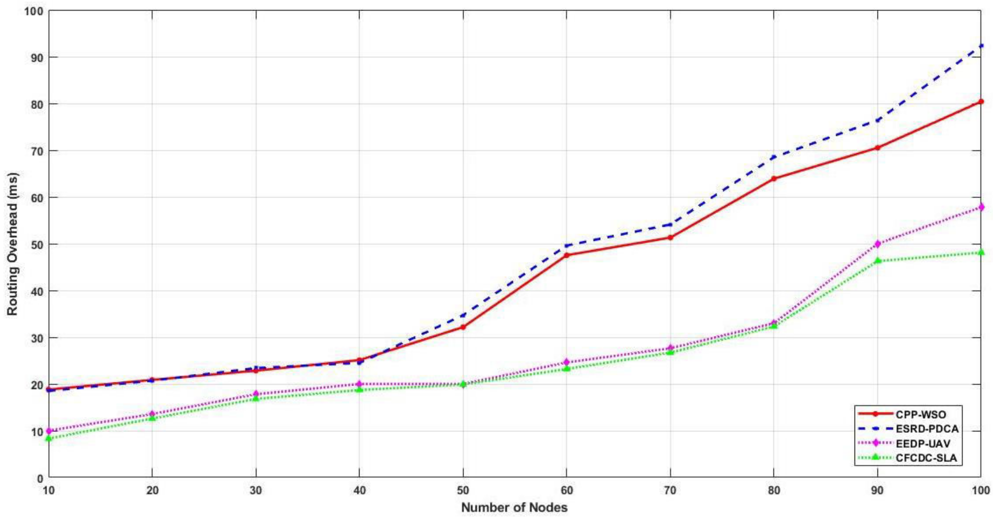

Figure 8: Effect of Node Density on Routing Overhead in CFCDC-SLA with CPP-WSO, ESRD-PDCA, and EEDP-UAV Algorithm

5. Conclusion

In this paper, collision-free and consistent data collection using SOA based LDPC approach (CFCDC-SLA) was developed for the UAV-assisted LoRaWAN based network.There were two stages to the proposed CFCDC-SLA algorithm's operation. First, we used the Seagull optimization algorithm as a collision-free scheduling algorithm. Secondly, we implemented a low-density parity-check (LDPC) system to ensure error-free and consistent data gathering. The CPP-WSO, ESRD-PDCA, and EEDP-UAV algorithms have all been compared against the performance of the proposed CFCDC-SLA algorithm, which was implemented using NS2 software. According to simulation studies, CFCDC-SLA achieves a higher data success rate and network throughput, while also achieving lower communication delays, energy efficiency, and routing overhead.

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