Journal of Information Systems Engineering and Management
2025, 10(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Relay Selection Technique for Energy-Efficient Data Transmission Policy for UAV-Assisted LoRaWAN

Mrs. J.Vijaya Barathy[1]*, Dr. K. Kamali[2]

[1]*Research Scholar (Part-Time), Department of Computer and Information Science, Annamalai University, Tamilnadu.*
barathyviji01@gmail.com

[2]*Assistant Professor/Programmer, Department of Computer and Information Science, Annamalai University, Tamilnadu.*
rmkmanikandan@yahoo.co.uk

ARTICLE INFO

Received: 28 Sept 2024
Revised: 26 Nov 2024
Accepted: 14 Dec 2024

ABSTRACT

An unmanned aerial vehicle (UAV), is an aircraft that does not have a human pilot and is controlled either independently by the aircraft's computers or by remote control. Because of their high mobility, FANETs are often used in UAVs because they can disrupt communications as well as network stability due to frequent topology changes. In-depth exploration and implementation of UAV network development, concentrating on diverse topologies such as star, multi-star, and network configurations, we developed the Energy-Efficient Data Transmission Policy for UAV (EEDTP-UAV) model. It emphasizes mobility, energy efficiency, UAV distance control, and road availability in the context of Flying Ad-hoc Network (FANET) technology development. Special attention is given to path optimization techniques and different link types, which are crucial for effective UAV communication. By using a relay-based energy-efficient process, off-grid user connections are optimized according to energy consumption meters, and data is collected cooperatively between the UAV cluster and the mobile synchronous node, providing equal energy usage and efficient data transmission. Due to its flexibility and adaptive nature, the proposed algorithm is well-suited for real-time UAV swarm operations that tackle dynamic path planning, and energy efficient communication methods such as airborne navigation or crowd control. Compared with existing model EEDS, DSSPCA, EEUCH, and ESRD-PDCA models with our proposed EEDTP-UAV model. By the following parameters communication delay, energy efficiency, data success rate, throughput, and routing overhead have been calculated.

Keywords: Energy-Efficient Data Transmission, Particle Swarm Optimization (PSO), Unmanned Aerial Vehicle (UAV) and UAV Path Optimization Algorithm.

INTRODUCTION

In the rapidly evolving landscape of technology, the convergence of Internet of Things (IoT) systems and Unmanned Aerial Vehicles (UAVs) represents a significant leap forward in data collection, analysis, and decision-making capabilities. This integration, known as UAV-assisted IoT, leverages the strengths of both technologies to enhance various applications and industries [1].

Unmanned aerial vehicles (UAVs), also known as drones, are aircraft that fly without a human pilot present. They are equipped with an array of sensors and cameras, which allow them to gather high-resolution data from diverse environments. In contrast, the Internet of Things (IoT) refers to a network of networked devices that exchange data and communicate online. IoT systems collect, transmit, and analyze data to enable smart decision-making and automation.

The integration of Unmanned Aerial Vehicles (UAVs) with Long Range Wide Area Network (LoRaWAN) technology represents a ground-breaking advancement in wireless communication and data collection. This fusion, known as UAV-assisted LoRaWAN, leverages the unique strengths of both UAVs and LoRaWAN to enhance connectivity and data transmission over long distances and challenging environments. Energy efficiency in UAVs (Unmanned Aerial Vehicles) is crucial for maximizing their operational capabilities and extending their flight times. Several factors contribute to energy efficiency, from design considerations to operational practices. Here's an overview of how energy efficiency can be achieved and improved in UAVs by Design Optimization, Battery Technology, proper Power Management, UAV path Planning and Operation, Data load Considerations and Other Environmental Factors [2-3].

In this paper, the proposed model Energy-Efficient Data Transmission Policy for UAV (EEDTP-UAV) model, that works to minimize the transmission energy consumption of the nodes and ensure timely data collection to UAV and also an energy efficient transmission policy is determined such that the optimum transmission mode is selected and the total transmission energy consumption of the nodes are minimized.

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 [4-5]. Techniques for error detection and repair are used to guarantee consistent data collecting.

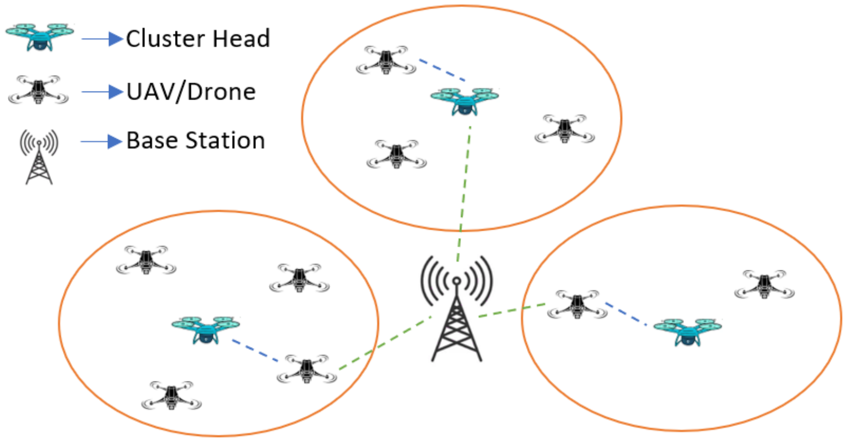

Figure 1: Network Model of UAV assisted LoRaWAN

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, deciding 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.

The remaining portions of this paper are arranged as follows: The prior study on Relay Selection Technique for Energy-Efficient Data Transmission policy 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.

EXISTING SYSTEM

In [6], The use of a social learning approach and fully automatic max-min colony algorithm (MMACO) to improve the self-management of drone swarms has been proposed as an improvement. It starts with three colonies, with three randomly placed drones, and selects the best drone to guide through the multi-agency system (MAS). The algorithm organizes these UAVs into formations and synchronizes them into a swarm controlled by dynamic leader selection. The hybrid approach is deemed superior to the non-dominant genetic allocation algorithm II (NSGA-II), which offers better convergence and shorter route planning.

In [7], explores a UAV-aided hybrid FSO/RF backhauling system to enhance B5G networks, particularly during adverse weather conditions that degrade FSO performance. A UAV is deployed to assist a ground base station (GBS) experiencing reduced backhaul capacity due to weather attenuation like fog. The GBS, typically connected to a macro-base station (MBS) via FSO, uses the UAV to offload users and maintain data transmission reliability. A matching game theory and reinforcement learning framework optimize UAV deployment and bandwidth partitioning to maximize system throughput. Real weather data from Edinburgh and London demonstrate the proposed scheme's effectiveness over traditional methods.

In [8], a rescue task distribution model using multiple UAVs has been developed to aid in post-earthquake search and rescue (SAR) operations. This model aims to lower drone emissions, reduce costs, and accelerate the recovery process. A new type of algorithm, PSOGWO, is a combination of particle swarm optimization (PSO) and gray wolf optimization (GWO), enhanced by a transformation, nonlinear transfer factor, individual update strategy, and dynamic weighting. PSO and GWO are examples of where the model has been tested in a case study. The analysis focuses on the sensitivity of UAV capability to factors such as rescue time and costs to develop VRP models for vehicle routing problems (VRP) and improve rescue strategies for SAR operations.

In [9], a multi-UAV guidance planning algorithm with advanced processing capabilities, known as PPSwarm, is designed to handle challenging terrain and obstacles. The RRT* algorithm is utilized by PPSwarm to quickly determine the first feasible route, and then a priority scheduling method is employed to facilitate drone cooperation. The randomization strategy maximizes the diversity of particle swarms and avoids local optimal traps. PPSwarm outperforms algorithms such as DE, PSO, ABC, GWO, and SPSO in terms of path quality, transition speed, & processing time for unconventional conditions according to experimental results. Additionally, PPSwarm demonstrates excellent scalability and processing capability in large-scale experiments with 500 UAVs.

In [10], the unfeasibility of human flight in challenging geographic conditions necessitates the planning and tracking of UAV routes. It uses the combined Harris-Hawk optimization (HHO) and GWO algorithm to optimize the route planning, ensuring obstacle avoidance and minimal energy and time consumption. The hybrid HHO-GWO algorithm effectively avoids local minima and achieves rapid convergence. The study also examines the impact of UAV mass change uncertainty on path planning and tracking. Compared to PSO and GWO, the proposed approach demonstrates superior performance, generating fast, safe optimal paths and ensuring efficient quadcopter tracking with minimal energy and time usage.

In [11], the authors introduced SSGWO technique that use gray wolf optimization algorithm which used for tracking UAVs in 3D agriculture. This algorithm uses a nonlinear transfer factor founded on trigonometric functions to equilibrium local and global searches. A method for achieving faster convergence has been devised using distance matching, and a simulated annealing (SA) based position update strategy is integrated to enhance the search process. A B-spline curve ensures path smoothness and feasibility. Simulation results demonstrate that SSGWO achieves better convergence accuracy, stability, and higher-quality paths compared to GWO, MGWO, IGWO, and SOGWO.

In [12], to improve the flight control of UAVs in difficult terrains, a fractional memetic computing approach known as Fractional Velocity Particle Optimization (FO-VPPSO) is utilized. The adaptive fractional order (FO-VPPSO) and rate-limiting approach are utilized by the organization, which is a significant challenge for conventional PSO algorithms due to their fast convergence and poor balance between exploration and exploitation. This hybrid algorithm optimizes flying path length, reduces terrain navigation costs, and prevents collisions. Simulations and benchmark tests demonstrate FO-VPPSO's superior convergence, solution optimality, and performance in complex terrains, improving fitness functions, flight length, terrain costs, and collision avoidance compared to PSO and VPPSO.

In [13], an improved algorithm for UAV path planning in urban pipe corridors syndicates using a accommodating game model founded on Nash trade-off theory, they optimized spherical vector particle swarm optimization (SPSO) and differential evolution (DE). A 3D network map of the city's pipelines is produced with a high level of accuracy, and supplementary information is provided to transform route planning into an optimization problem. Cost-effectiveness enhancement for UAV surveillance techniques can be achieved with a hybrid GSPSODE algorithm. Comparisons with SPSO, DE, GA, and ACO show GSPSODE's superiority, though experimental parameters and conditions can impact accuracy. The RflySim platform emulates UAV inspection routes in urban pipeline systems.

In [14], multi-UAV dynamic task scheduling for disaster relief operations, such as emergency communications, supply delivery, and disaster mapping. It constructs a multi-constraint mathematical model considering task demands and UAV capabilities, with objectives to maximize scheduled task profit, minimize time consumption, and balance tasks among UAVs. A method of weighted summation is used to optimize the multi-objective problem into a single-objective one. It introduces a new, dynamic job scheduling method using purely hybrid contract protocol, with exchange, replacement contracts, and buy-sell agreements. Extensive simulation proves that the method is effective even in situations where unexpected operations, interruption, and floor failure are present.

In [15], a good planning strategy for UAV teams performing area coverage operations in 3D space. It addresses problems such as uneven distribution of work, low capacity, and high effort. This area is then divided into sub-areas using the improved C-clustering algorithm for task allocation. The UAV task paths are then planned using a PSO hybrid ant colony (PSOHAC) algorithm. Simulations verify the scheme's feasibility and superiority, showing that it achieves full area coverage and efficient task allocation. The proposed method improves balanced energy consumption efficiency by up to 21.9% and overall energy efficiency by up to 7.9% compared to related algorithms.

In [16], the wireless network represents the uneven distribution of traffic in mobile networks and uses drones as relays to reduce congestion. It jointly optimizes UAV positioning, user communication, spectrum, and power distribution to maximize user registration. Genetic-based algorithms optimize UAV position, while a branch-and-bound method simplifies user association and spectrum allocation. A power distribution switch is proposed based on the near-inverting concept. Simulations demonstrate the superiority of the UAV-assisted network over terrestrial networks in both utility and throughput, with significant performance improvements compared to other schemes.

In [17], a photovoltaic solar system into UAVs to address safety and flight autonomy challenges. It consolidates solar cells without compromising aerodynamic efficiency and analyses the potential of solar resources in fixed-wing aircraft for video surveillance applications. The investigation identifies the optimal position of both wings and aircraft by using computer simulation tools to examine their charge-discharge model. It aims to make the battery charge more efficiently by putting in photovoltaic cells; results and conclusions on this can be found at length in the article's final section.

In [18], lightweight hydrogen fuel cell-powered rotary-winged aerial vehicles for urban transportation, can carry either unmanned cargo or one passenger. The optimization process integrates aerodynamic and propulsion system sizing to meet performance requirements, achieving a specific range and endurance suitable for urban air transport.

In [19], using PSO to design high-quality control mechanisms for an innovative hybrid thermal management system (IHTMS) in electric batteries (EV). The aim is to reduce low-efficiency temperature periods during EV startup and maintain optimal temperatures for PEMFCs and batteries, improving travel range and power output. PSO-based control strategies outperform rule-based (RB) methods in reducing temperature rise time and average temperature errors for both PEMFCs and batteries under various driving cycles (WLTP and NEDC). Future work involves experimental verification of IHTMS integration into hybrid-energy EVs.

In [20], a Mobile Edge Computing (MEC) system architecture for joint-UAV surveillance tasks with low battery power and computing resources. It uses a helicopter (UH) as a MEC server to provide data services for surveillance UAVs, aiming to reduce the burden of effort and delay. The bat algorithm (IBA) is better for solving computational strategy problems, demonstrating superior accuracy, stability, and efficiency compared to heuristic algorithms like PSO and the basic Bat Algorithm (BA). Simulation experiments confirm the effectiveness of IBA in reducing energy consumption and task execution delay for multi-UAV operations. In [21], energy management for the aircraft's fuel-electric system is intended to maximize the engine' cab working area, regulate dynamic dynamics, and maintain control over the battery charge. It employs the maximum likelihood method for fuel consumption efficiency curve identification and real-time load power estimation. Multi-objective model predictive control integrates engine and battery characteristics, with fuzzy control adjusting weight coefficients dynamically. Simulation experiments confirm the effectiveness, showcasing improved economy, battery management, and system stability compared to pure fuel drive.

In [22], the utilization of a convolutional neural network (MWSO-CNN) for war strategy prediction utilizes adaptive war strategies optimization and CNN to optimize war strategies. The MWSO technique adjusts hyperparameters for improved efficiency. Tested on real-world datasets, more cost-effective than current machine learning techniques, MWSO-CNN offers an affordable means of accurately forecasting energy usage and is beneficial to the energy sector and society. In [23], this is an extensive framework for UAV traffic control in small-scale urban areas, encompassing everything from cluster-based route planning and conflict detection (CD&R) in unmanned aerial vehicle traffic management (UTM) to spatial resource allocation methods. The framework employs the Saturated Fast-Marching Square algorithm for path planning and proposes four UTM models for efficient airspace resource allocation. The Batch Optimization (BO) model strikes a balance between computational tractability and system optimality. An adapted Vickrey-Clarke-Groves (VCG) mechanism incentivizes truthful information reporting by UAV operators. The scalability and effectiveness of the proposed framework are demonstrated through a numerical analysis conducted in the San Francisco region.

In [24], aerial surveillance using the Joint Topology Control and Routing (JTCR) protocol, which involves UAV teams, addresses issues of optimal distribution and data routing. The protocol integrates virtual force-based mobility control, energy-efficient fuzzy clustering, and topology-aware Q-routing to ensure stable connectivity, efficient data aggregation, and optimal routing. Performance analysis demonstrates superior tracking coverage, connectivity, and energy efficiency compared to existing protocols, achieved through realistic UAV mobility control with reasonable control overhead.

In [25], using MSGA-DE and HNS-IBWO, we can use a planning model and two-stage metaheuristic algorithm to improve the distribution and collection of medical devices in closed-loop logical networks during outages. Comparing the effectiveness of MSGA-DE for UAV trajectory planning with HNS-IBWO for more complex optimizations is demonstrated by this comparison. Simulation results in a closed community at the end of Shanghai confirm that the model is effective for tasks such as hybrid flights of aircraft, multi-objective search, and global search, providing 'the right solution' for planning UAV traffic during the pandemic shutdown.

PROPOSED SYSTEM

3.1 Proposed EEDTP-UAV Model

The proposed EEDTP-UAV system has been classified into seven step procedure to carry full set of operation. Basically, this EEDTP-UAV was classified into two working operation, based on Energy efficient management and Reliable Data Transmission.

3.2 LoRaWAN routing Protocol

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. The Application Server will receive the packet as if it was sent directly from the initial node, and its energy remains reliable throughout as part of a single hop network within LoRaWAN. The different components within the network: blue for gateways, dark orange for RN1 (located near a gateway), and light orange for other RNs that receive updates from neighbour RNs (such as RN1) and then transmit their own updates.

3.3 Mobile UAV Placements

A new approach for placing mobile UAVs most effectively. This method utilizes a cyclical multiple access strategy, where a mobile UAV equipped with a base station is used to improve wireless connectivity and communication quality for distributed ground terminals. By using drones with high-speed capabilities, this telecommunication method enhances communication between sources and endpoints. To achieve this, the trajectory and power distribution of the UAV are optimized for optimal performance. However, only two studies considered the use of a single drone and developed a simple method for it. The proposal suggests a round-the-world path with 'an essential point on the ground' for low-power communication between UAVs and ground nodes. The goal is to optimize the UAV approach to create a balance between information power and effort.

3.4 Air-to-Ground Path Loss Process

By utilizing the air-to-ground path loss model, it is possible to estimate the distance between the mobile node (MN) and the UAV- Multi-Access Edge Computing (MEC) server. MN(i) can be found at the coordinates of the positions x_i, y_i, and zero in the three-dimensional space. In the time slot $'t'$, MN i and UAV-MEC server j are separated by $r_{i,j}(t)$. The UAV-MEC server's long route can be used to determine the 3D distance between MN(i) and the UAF-MCE server $'j'$. Line-of-sight (LS) and non-line-of-see (NLT) communication modes are utilized by this model to enable wireless communication between two devices. The methods for consolidating LoS and NLoS can be mathematically represented:

$$d_{i,j}(t) = \sqrt{x_i - x_j(t))^2 + (y_i - y_j(t))^2 + h^2} \quad (1)$$

The velocity of light and the incidence of the carrier wave are denoted by c and f, respectively. The natural factors ηLS and ηNLS are specific for the 'LS' and 'NLS' transmission methods, respectively. By using these parameters, the below equation can formulate that reflects the likelihood of 'LS' occurring between MN(i) and the UAV-MEC server $'j'$.

$$PL_{Los} = 20\ log d_{i,j}(t) + 20 \log f + 20 \log \frac{4\pi}{c} + \eta_{Los}, \tag{2}$$

$$PL_{NLos} = 20\ log d_{i,j}(t) + 20 \log f + 20 \log \frac{4\pi}{c} + \eta_{Los}, \tag{3}$$

$$P(LoS) = \prod_{n=0}^{m} \left(1 - exp \left(\frac{\left(h_j - (n + \frac{1}{2}) \frac{(h_i - h_i)^2}{(m+1)} \right)}{2\gamma^2} \right) \right) \tag{4}$$

$$m = \llcorner((h_i - h_i) tan\theta \sqrt{\alpha\beta - 1}, \tag{5}$$

h_i is the height of the UAV-MEC server while h_j is its height. It should be emphasized that the system's frequency does not affect the geometry of the line-of-sight (LS). The probability function for 'LS' links can be represented by an S-curve, with constants a and b being determined by the breeding environment, or in high places. $\omega = \arctan\left(\frac{h}{r_{i,j}(t)}\right)$ represents the maximum angle between MN(i) and UAV-MEC server 'j' at time slot 't' along the counter path. Then the probability function for creating a non-line-of-sight (NS) link can be expressed as the average path loss (APL) of the system in a time slot 't' can be calculated using equations (2), (3), (6), and (7) in equation (8). Using basic algebraic operations, we get:

$$P(LS) = \frac{1}{1 + \alpha \exp\left(-b(\omega - 1)\right)'}, \tag{6}$$

$$P(NLS) = 1 - P(LS) \tag{7}$$

$$PL_{i,j}(t)) = P(LS) \times PL_{LS} + P(NLS) + PL_{NLS} \tag{8}$$

$$PL_{i,j}(t)) = \frac{\eta_{LoS} - \eta_{NLoS}}{1 + a \exp\left(-b\left(\arctan\left(\frac{h}{r_{i,j}(t)}\right) - a\right)\right)} + 10 \log\ (d_{i,j}(t)^2) + 20 \log(f) + 20 \log\left(\frac{4\pi}{c}\right) + \eta_{NLS}, \tag{9}$$

In this scenario, we are using the equation (1) to represent the signal strength between MN(i) and UAV-MEC server $'j'$ at time $'t'$. MNs are assumed to possess equal transmission power. Therefore, the signal-to-noise ratio between MN(i) and UAV-MEC server $'j'$ at time slot 't' is given by p^{i^2}/σ^2, where p_i is the transmission power of MN(i) and σ_2. The noise effect is the ground to airborne (GA) data transfer rate between MN(i) and UAV-MEC server $'j'$ at slot $'t'$ and is determined by this equation. To determine the average data transfer rate for MN(i) overall 'T' cycles, one needs to multiply the job buffer request rate by each job request's data size, such as l_i, λ_i.

$$SNR_{i,j}(t) = \frac{P_i}{PL_{i,j}(t) \times \sigma^2}, \tag{10}$$

$$R_{i,j}(t) = B\ log_2(1 + SNR_{i,j}(t)) \tag{11}$$

$$R_{i,j}(t) = \frac{1}{P} \sum_{t=1}^{P} R_{i,j}(t) \tag{12}$$

$$T_{i,j}^{Trans} = \frac{1}{R_{i,j}} \tag{13}$$

$$T_j^{total} = \sum_{i=1}^{M} A_{i,j} \lambda_i T_{i,j}^{Trans} \tag{14}$$

It is assumed that all tasks requested from the MD i are sent through the output of the G2A channel is high on the UAV-MEC server j. The G2A data transfer delay, $T_{i,j}^{Trans}$, depends on the processing data size, l_i, and the data transfer rate, $R_{i,j}$. By multiplying the download request rate of λ_i with the equation $T_{i,j}^{Trans} = l_i/R_{i,j}$, one can regulate the entire data transmission delay for MNs associated to the UAV-MEC server. By using the equation $E_j^{trans} = l_i * \lambda_i$, it is possible to determine the energy required to transfer tasks between MN(i) and UAV-MEC server $'j'$. Total energy ingesting for all MNs connected to the UAV-MEC server $'j'$ can be determined by multiplying each task's data size, l_i, with its corresponding task offload request rate, λ_i.

$$E_j^{trans} = P_i T_{i,j}^{total} \tag{15}$$

$$E_j^{total} = \sum_{i=1}^{M} A_{i,j}\lambda_i\, E_{i,j}^{trans} \quad (16)$$

3.5 Optimal Path Planning Process

The meta-heuristic algorithm, inspired by nature, is utilized to determine the best route for a swarm of UAVs. As the UAVs operate together, they come across various obstacles that can hinder the network's efficiency. The proposed algorithm draws inspiration from swarm algorithms, which aim to find the most efficient path. It is complemented by a well-planned approach to manage data transmission and communication throughout the network. In the dynamic environment of the time, where multiple UAVs operate as a swarm, their distance and position must be continuously updated to find the optimal route.

Moreover, if there are any changes in surveillance tactics, the UAV swarm network should be able to adapt without compromising its performance. The current algorithms for planning paths prioritize taking advantage of existing information rather than exploring new possibilities within the search space. Consequently, these algorithmic methods that are inspired by nature do not yield the best outcomes in a constantly evolving search landscape. The system model showcases a reliable routing plan that incorporates energy efficiency and benefits from PBFT smart contracts. By keeping track of neighboring activity details, it makes it simple to identify and remove malicious nodes while also ensuring that all node registrations are registered within the network.

Ethereum's growing popularity allows for decentralized applications and smart contracts in energy efficiency and the integration of its unique features. During the tracking process, information about nodes' positions with their location is monitored along with that of neighboring node information. Smart contracts are used to bind and authorize nodes in the network, ensuring their legitimacy through certificates. Each node is assigned a $gasLimit$, indicating the maximum number of resources it can handle.

Using Ethereum, the proposed agile model can verify the identity and availability of nodes in the Swarm network through efficient smart contracts. It provides the ability to identify reliable and malicious devices in the network. Each device is assigned a unique ID and $gas\ limit$ as an allocative resource after signing up for the drone network. A specific throttle level is used by the server node in the smart contract to control communication between UAV nodes and base stations for better data transmission. A new node must be authenticated by the server before joining, as only the trusted server nodes can add or remove noise noses from their network. The smart contract manages the identity of each registered node, allowing for monitoring of their activities. By removing the server from the network, it can shield against low power nodes in its network UAV due to energy efficiency behavior.

3.6 UAV Path Optimization Algorithm

The main problem of the current algorithms is that they are not able to provide the best way in unpredictable and dynamic environments. Environmental factors like wind, smoke, or threats to communication power can pose a significant problem when work is not completed. To address this issue, the proposed UAV Path Optimization Algorithm not only achieves an optimal path for UAVs but also ensures reliable data transmission between UAVs and from UAVs to GCS. The flow diagram in Figure 2 illustrates how UAV Path Optimization Algorithm finds the optimum path for a single UAV. Additionally, Algorithm 1 generates an optimal path for a group of UAVs. In contrast, at first, the suggested system creates an optimal path, and if one node is targeted, other nodes that no longer belong to the network are created, thus safeguarding the system. Energy efficiency and data reliability are ensured through the collection of information about each UAV node's location, proximity to launch sites, energy consumption, and smart contract data of strength.

The algorithm's performance is enhanced by incorporating a gene expression method. A method of genetic reproduction through transposition and mutation has taken the place of the traditional algorithm. A global optimization product strategy is implemented using a transition manager. Another development of the algorithm was achieved by introducing a copy of the switch. There are two binary and exponential methods to determine the transition probability. The mutation probability is controlled by an evolutionary mutation algorithm. To enhance the algorithm's efficiency, various benchmark problems were validated. These problems were classified as low or high based on a well-known function. Due to the random nature of metaheuristic algorithms, a single run cannot accurately assess its performance. The approach's performance was improved by conducting multiple trials with independent population initialization. Each obstacle X in the simulation is assigned a risk level, denoted by the constraint μ.

$$f(x) = \frac{1}{(2\pi)d}/2|\sum|1/2\exp\left[-\frac{1}{2(X-\mu)}\right] \quad (17)$$

By calculating the area X_{ti}, one can determine whether it is possible to avoid collisions with static or dynamic obstacles. The center point of every dynamic is determined by creating a random number, i. This data is defined using alpha symbols to define the risk zone and indicate the UAV's position at each step. To convert the equality constraint into a probability control, a different rule is used. Integrating qualified uncertainty helps solve a mutual uncertainty tricky with UAVs that can be solved using the subsequent equation: The 'n' space is resolute using the decision space- n, through the optimization algorithm minimizes the space. which uses less energy. The UAV node's physical motion is represented by D_t, and its search motion can be expressed as F_t. Adjacent UAV nodes are called N_t.

$$\frac{D_{xt}}{d_t} = N_t + F_t + D_t \tag{18}$$

Algorithm 1 - UAV Path Optimization Algorithm

which involves initializing various parameters such as $N_{maximum}$ and $D_{maximum}$.

For D1=1 to P do

For D2=1 to t do

$X_{D1,D2} = 1 + rand$ mod M, Memory initialization

$Y = Turns, PL\ (D1, D2), z$

$Define\ population\ size\ (p), neighbors\ list\ (NL), energy\ E$

End for

Appraise the fitness function (FF) for individually node

End for

The algorithm then goes through a loop,

evaluating the fitness function for each node and,

finding the best solution,

It continues to iterate while the number of nodes (N) is less than or equal to $Nmax$,

For D1=1 to P do

Accomplish the fitness Calculation by

$x_i(D1 + 1) = x_i(D1) + y + PL(i, j)$

End for

Find the best solution

Sort and find X_{best}, where best $\epsilon(1,2, \ldots, S)$

$N = N + 1$

If $Xbest$=y

Find $Xbest + 1, where\ best\ \epsilon(1,2, .., s)$

Return $Xbest1$

Within each iteration, it calculates the fitness and performs exploration to improve the solution,

Finally, it returns the best solution found after all iterations are completed.

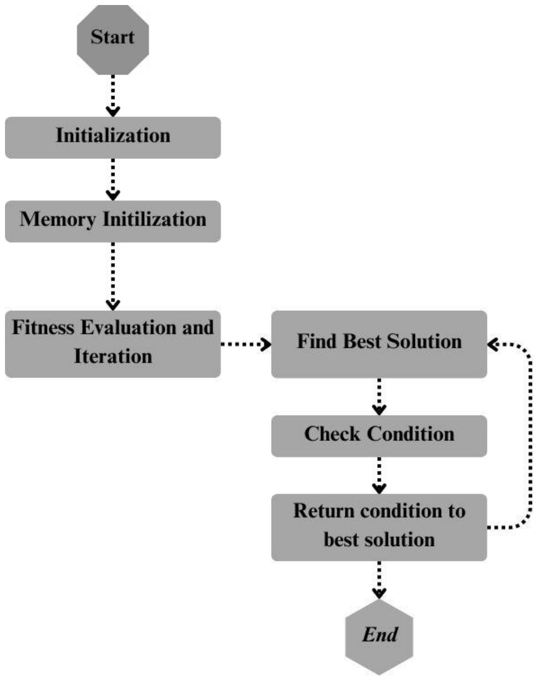

Figure 2: The process of UAV Path Optimization Algorithm.

3.7 Efficient Relay Section Process

The Energy-Efficient Relay Selection Algorithm aims to re-establish the connection for users outside the network by efficiently pairing them with relays (located inside the network). Our approach focuses on selecting the most energy-saving association scheme for outside users. This is achieved by determining a preference list for both relays and outside users based on their consumed energy. The preference list is generated by sorting the utility function in descending order. When an outside user requests an association, the relays refer to their preference list and maximum user capacity to decide whether to accept or reject the request. The priority is given to relays that consume the least amount of energy. The utility function calculates the benefits for an outside user $i \epsilon u_I^{out}$ to connect with a candidate relay $j \epsilon u_I^{int}$, and for the relay j to accept the request from a user i.

$$U_i(j) = U_j(i) = (p_{i,j}^{min} + (p^{cir})^{-1} \tag{19}$$

The energy consumption of the static circuit at SU is represented by p^{cir}. Additionally, $p_{i,j}^{min}$ denotes the minimum transmit power required for the user i to meet the QoS standard while connected to a relay j. This value is determined by the following calculation: Our study presents a many-to-one matching game to depict the association between external and internal users. In this game, the participants are represented as external and internal users, each with their ranking of preferences. The ultimate association outcome is determined based on these preference rankings.

$$p_{i,j}^{min} = 2^{(\frac{R_{min}^I}{B_{r-1}})} \sigma^2 / h_{i,j} \tag{20}$$

Each remote user or relay has a fully switched two-way connection that is mirrored and switched, with the main priority being an unmodified wire. This means that this connection is defined across the entire set of relays and external users. For every external user $i \epsilon u_I^{out}$, their preference order over all possible relays is determined by their likelihood of selecting a relay j over relay j'. Similarly, for every relay $j \epsilon u_I^{int}$, the preference order of overall outside users is determined by their likelihood of being selected by the user i.

$$j \Delta_i j' \Leftrightarrow U_i(j) > U_i(j)' \tag{21}$$

This indicates that the relay j is the preferred choice to act as the relay for the user i. Our proposed algorithm for efficient relay selection is outlined in Algorithm 2. The initial step involves sharing channel rights and other relevant information between relays and users. Each user and relay creates a list of priorities based on a calculator (19). Subsequently, each user requests a connection with their preferred relay. The preferred applicant is accepted by each relay while the remaining applicants are rejected. Rejected applicants then propose to their next preferred relay. The communication is terminated when the relay is connected by all external users.

Algorithm 2: Selecting Energy-efficient Relays for External node.

First prepare the proclivity list for each external node and relay, using formula (9). Also, set the list of external nodes accepted by the relay as $u_I^{out,rejected} = u_I^{out}$.

While $u_I^{out,rejected} \neq \emptyset$, do:

For each external node $i \epsilon i_I^{out}$ do,

Demand to attach to their chosen relay indicated by (21).

For each relay $j \in u_I^{in}$ do,

Sort the candidates in descending order based on their favorite list as shown in (22).

Though the quantity of accepted node at relay ‘j’ does not exceed $'N_{Max}'$ do

Admit the favored applicant and add them to $u_I^{out,accepted}$. Then remove them from the favorite list of relays j.

End

End

Individually rejected node updates their favorite list by eliminating their favored relay.

End.

3.8 Efficient Data Collection Process among UAVs

This model is a method used to collect data between a group of UAVs that includes a mobile sink node. This process has several steps. The mobile sink node and the UAV cluster partner together to establish the shortest route for the telephone line. Subsequently, the sink node discovers its position data. Afterward, the UAV team utilizes the shortest route to retrieve data from all the mobile sensors located in the WSNs. The mobile sink node can expand the area of the UAV's sensing range by rerouting its communication antenna, which will enhance its data search capabilities.

The initial step involves implementing an algorithm called enumerated pruning to identify the optimal path for UAV movement, considering input from both the UAF cluster and the mobile sink node. In the second step, a positioning algorithm is used by the mobile sink node to determine an optimal route that uses energy more efficiently. In step three, a switching mechanism is used to complete parameter conversions and collect data by following the optimal path while accessing sensing nodes in multi-hop mode at the mobile sink node. By adjusting the communication radius of the mobile sink node and balancing energy consumption throughout, step four allows for an increase in the sensing area. The UAV cluster plays a role in confirming energy balance and calculating future communication radius for data collection cycles.

Step 1. Adjust establishing the parameters of each node, such as the communication range, before initiating the initial data collection. The communication radius is initially adjusted to match the maximum data transmission distance established in step 5 during the following data collection cycles.
Step 2. Plan the route for the mobile sink node using either algorithm truncation algorithm or the algebraic division algorithm.
Step 3. Calculate by using (16) to compute the average amount of data to be gathered, it can calculate another way to estimate the communication radius of the sensor node. Additionally, determine the coverage area by formula (8).
Step 4. The likelihood of a successful data transfer can be determined using the second theory. In that case, the setup method for the mobile sink is very good. If not, it needs to be adjusted. After completing communication, mobile nodes in the network send out the remaining capacity to their mobile sink node through several hops.
Step 5. Utilize Theorem 4 to calculate and optimize by adjusting the communication radius and returning it to its original location, the remaining energy of the synchronous node is utilized. The algorithm is terminated when the synchronous node's remaining capacity diminishes.

Algorithm can be summarized as follows:

Procedure 3: Procedure

Input: P transmission range $(P^{tr}, R_c, E_{elec}, N, \lambda, \varphi, \rho, \delta)$,

Output: Minimum required data transmission rate Q_{min}

While (node i is not empty)

{

calculate the maximum communication radius for $link[i] as\ R_{C\_max}$,

calculate the optimal node for $long[i]\ as\ node[i]$

Calculate the average successful data transmission rate for the node $i\ as\ Data_{suc\_rate}[i].node$

Calculate the value of A_i as X_i

increment i by 1

if $(p \rightarrow 1)$

calculate the optimal node for $long[i]\ as\ optimal.node[i]$

else

exit the loop

set the minimum required data transmission rate for $node\ [i].ms\ as\ Q_{min}$

}

Calculate the value of Q_{opt} using,

if (Q_{opt} is less than Q_{min})

update Q_{min} to be equal to Qopt

Output Q_{min}

else Output Q_{min}

The time complexity of the algorithm is now being examined. The first step involves transforming the nonlinear function into a linear one, with the best-case scenario resulting in all variables being transformed into linear relationships. This results in a time complexity of $O(n)$. If the pruning algorithm is employed in step 2, the time complexity will be $O(n)$. However, the time complexity of $O(n^2)$ increases when using a variable division algorithm. By using a circular method, the average value of the data that was obtained is computed in step 3, and the time complexity is $O(n^2)$. The fourth step in this paper deals with a data collection approach that uses linear parameters and collects data through sensor nodes in the network. As a result, the time complexity becomes $O(n^2)$. Finally, step 5 follows the same solution process as step 4, so it takes $O(n^2)$ time. In general, this algorithm has a time complexity of $O(n^2)$.

RESULT AND DISCUSSION

This area covers the outcomes of the EEDTP-UAV algorithm, which was shaped as Relay Selection Technique for Energy-Efficient Data Transmission policy for UAV-assisted LoRaWAN. The subsequent section provides a complete explanation of the findings and discussion of the suggested EEDTP-UAV approach. We implemented the EEDTP-UAV using the Network Simulator-2.34 (NS-2.34). The simulation sceneries 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

a) Communication Delay:

The time required for a message or signal to travel from the sender of origin to its receiver is known as communication delay. This includes delivery, routing, processing, and queuing delays. Networks and distributed systems can experience delays that hinder data exchange. In Figure 3, the communication delay performance is calculated for methods like ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV.

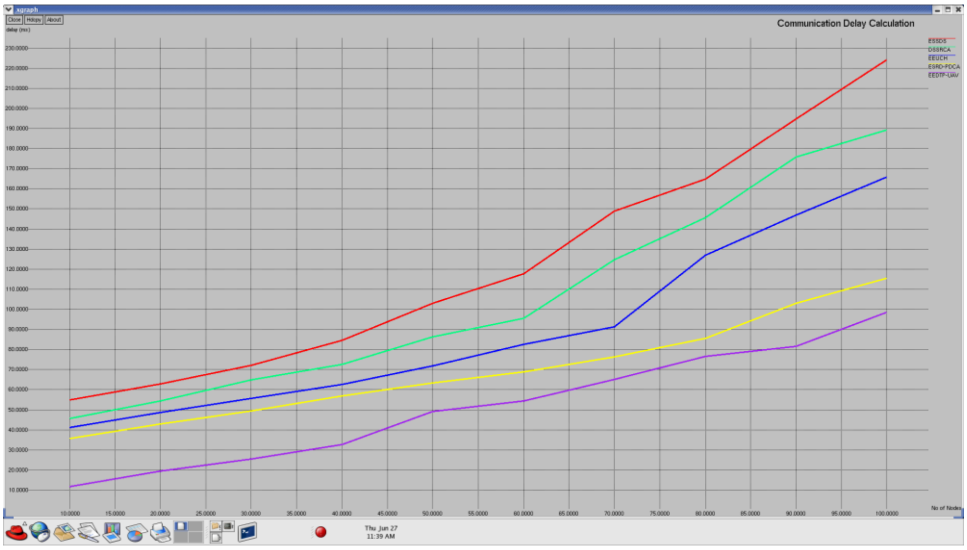

Figure 3: Effect of Node Density on Communication Delay in ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV algorithm

b) Energy Efficiency: Energy efficiency means less energy is required to perform that task or product. This involves optimizing processes, equipment, and systems to reduce energy consumption without compromising performance. Energy efficiency can lead to cost-effectiveness, environmental sustainability, and improved energy performance. In Figure 4, the energy efficiency performance is calculated for methods like ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV.

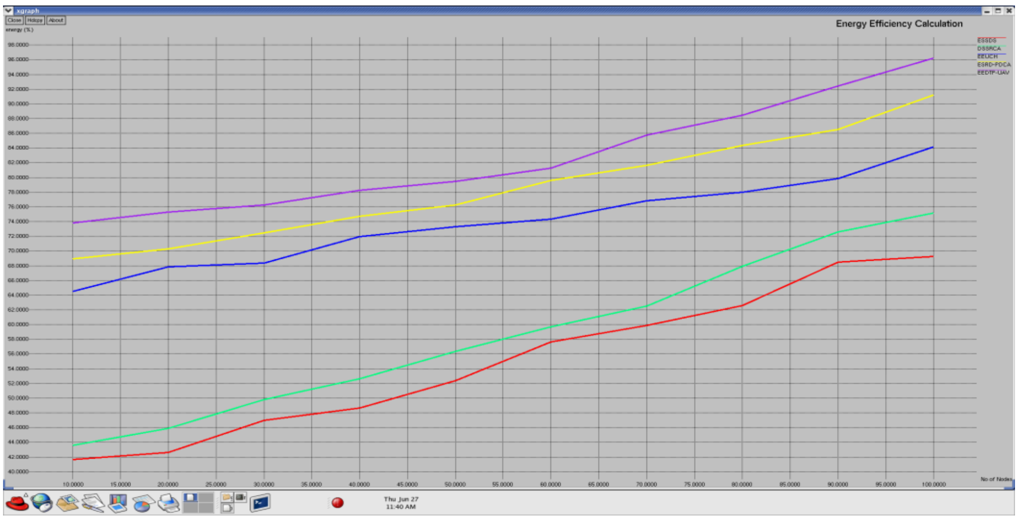

Figure 4: Effect of Node Density on Energy Efficiency in ESSDS, DSSRCA, EEUCH, ESRD-PDCA, with the proposed EEDTP-UAV model

c) Data Success Rate: Generally speaking, the data success rate refers to the percentage of transmitted information that is received and transmitted over the communication network. It evaluates the dependability and effectiveness of data transmission and considers potential errors or losses. Efficient and reliable network performance is indicative of a high success rate. In Figure 5, the data success rate performance is calculated for methods like ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV.

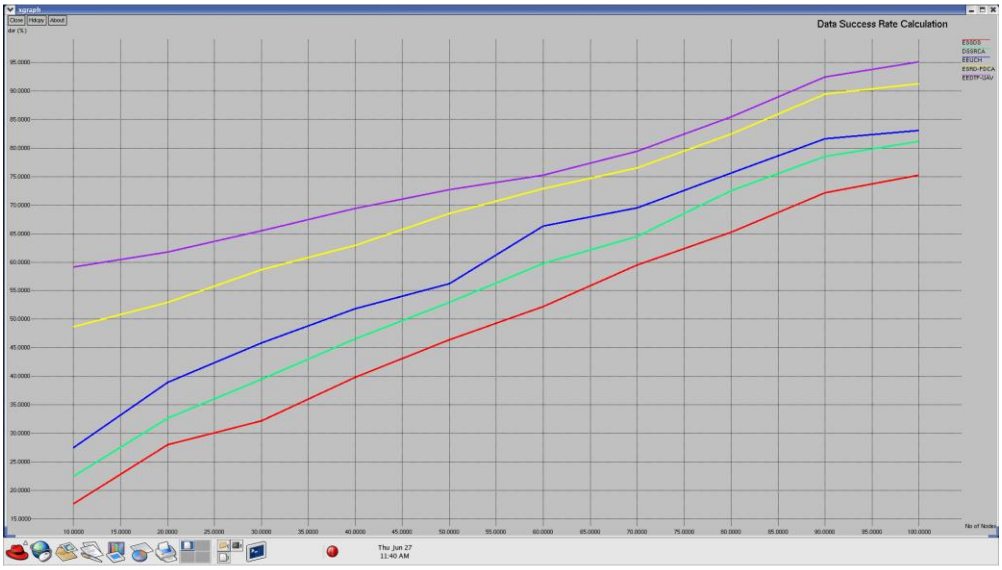

Figure 5: Effect of Node Density on Data Success Rate in ESSDS, DSSRCA, EEUCH, ESRD-PDCA, with the proposed EEDTP-UAV model

d) Network Throughput: By measuring the rate of data transfer between networks and their interconnections, throughput is defined. It is usually measured in bits per second or data packets per second. The efficiency of data transfer and network performance is indicated by high throughput. In Figure 6, the throughput performance is calculated for methods like ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV.

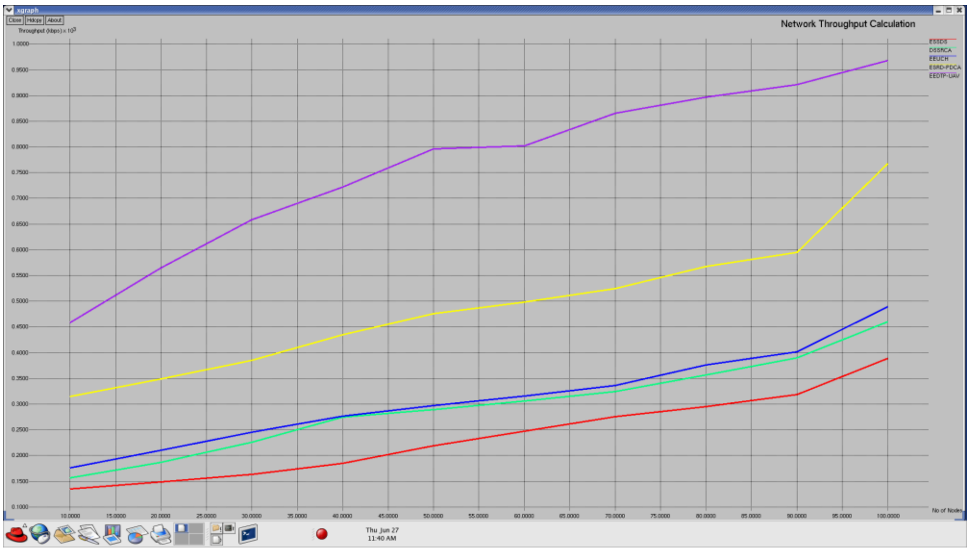

Figure 6: Effect of Node Density on Network Throughput in ESSDS, DSSRCA, EEUCH, ESRD-PDCA, with the proposed EEDTP-UAV model

e) Routing Overhead: The transfer of routing information between network nodes results in supplementary network traffic, which is known as routing redundancy. It contains control messages, updates, and other protocol-specific information necessary to maintain accurate routing tables. High routing costs may result in reduced efficiency due to the consumption of bandwidth and processing resources. In Figure 7, the routing overhead performance is calculated for methods like ESSDS, DSSRCA, EEUCH, ESRD-PDCA, and the proposed EEDTP-UAV.

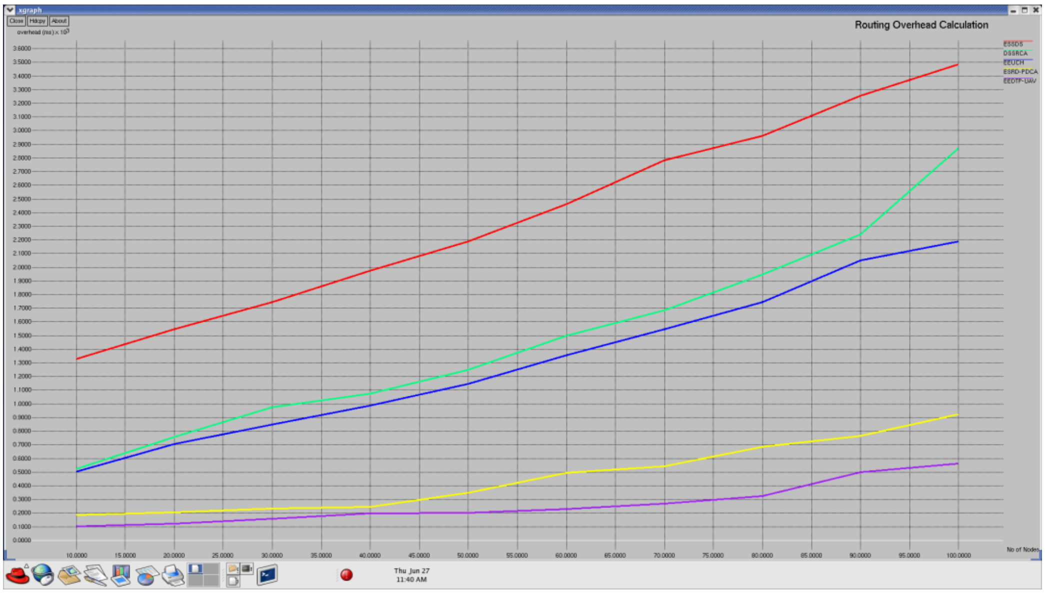

Figure 7: Effect of Node Density on Routing Overhead in ESSDS, DSSRCA, EEUCH, ESRD-PDCA, with the proposed EEDTP-UAV model

CONCLUSION

In this paper, Energy-Efficient Data Transmission policy for UAV assisted LoRaWAN was deployed using relay selection technique. Optimizing data collection processes, reducing power consumption, and improving overall efficiency in multi-hop UAV operations are achieved using computational pruning and variable separation techniques. The proposed work has been implemented using NS2.34 simulation tool. Using communication delay, energy efficiency, data success rate, throughput, and routing overhead parameters will enhance our proposed EEDTP-UAV model when compared with other existing techniques such as EEDS, DSSRCA, EEUCH, and ESRD-PDCA. According to simulation studies, EEDTP-UAV achieves a higher data success rate and network throughput, while also achieving lower communication delays, energy efficiency, and routing overhead.

REFERENCES

[1] Tao Lei, Yanbo Wang, et.al, “An Optimal Fuzzy Logic-Based Energy Management Strategy for a Fuel Cell/Battery Hybrid Power Unmanned Aerial Vehicle”, Aerospace, vol. 9, pp. 115, 2022, Available from: https://doi.org/10.3390/aerospace9020115

[2] Jinyan Yao, Yongbai Sha, et.al, “IHSSAO: An Improved Hybrid Salp Swarm Algorithm and Aquila Optimizer for UAV Path Planning in Complex Terrain”, Application Science, vol. 12, pp. 5634, 2022, doi: 10.3390/app12115634 Available from: https://doi.org/10.3390/app12115634

[3] Suping Zhao, Chaobo Chen, et.al, “Trajectory Planning of Aerial Robotic Manipulator Using Hybrid Particle Swarm Optimization”, Application Science, vol. 12, pp. 10892, 2022, doi: 10.3390/app122110892 Available from: https://doi.org/10.3390/app122110892

[4] Enrique Ballinas, Oscar Montiel, et.al, “Hybrid Quantum Genetic Algorithm with Fuzzy Adaptive Rotation Angle for Efficient Placement of Unmanned Aerial Vehicles in Natural Disaster Areas”, Axioms, vol. 13, pp. 48, 2024, doi: 10.3390/axioms13010048 Available from: https://doi.org/10.3390/axioms13010048

[5] Yi Zhang, Hongda Yu, “Application of Hybrid Swarming Algorithm on a UAV Regional Logistics Distribution”, Biomimetics, vol. 8, pp. 96, 2023, Available from: https://doi.org/10.3390/biomimetics8010096

[6] Muhammad Shafiq, Zain Anwar Ali, et.al, “A Multi-Colony Social Learning Approach for the Self-Organization of a Swarm of UAVs”, Drones, vol. 6, pp. 104, 2022, doi: 10.3390/drones6050104 Available from: https://doi.org/10.3390/drones6050104

[7] Muhammad Nafees, Shenjie Huang, et.al, “Backhaul-Aware User Association and Throughput Maximization in UAV-Aided Hybrid FSO/RF Network”, Drones, vol. 7, pp. 74, 2023, doi: 10.3390/drones7020074 Available from: https://doi.org/10.3390/drones7020074

[8] Dan Han, Hao Jiang, et.al, “Collaborative Task Allocation and Optimization Solution for Unmanned Aerial Vehicles in Search and Rescue”, Drones, vol. 8, pp. 138, 2024, Available from: https://doi.org/10.3390/drones8040138

[9] Qicheng Meng, Kai Chen, et.al, “PPSwarm: Multi-UAV Path Planning Based on Hybrid PSO in Complex Scenarios”, Drones, vol. 8, pp. 192, 2024, Available from: https://doi.org/10.3390/drones8050192

[10] Egemen Belge, Aytaç Altan, et.al, “Metaheuristic Optimization-Based Path Planning and Tracking of Quadcopter for Payload Hold-Release Mission”, Electronics, vol. 11, pp. 1208, 2022, Available from: https://doi.org/10.3390/electronics11081208

[11] Jianxin Feng, Chuanlin Sun, et.al, “A UAV Path Planning Method in Three-Dimensional Space Based on a Hybrid Gray Wolf Optimization Algorithm”, Electronics, vol. 13, pp. 68, 2024, Available from: doi: https://doi.org/10.3390/electronics13010068

[12] Abdul Wadood, Al-Fahad Yousaf, et.al, “An Enhanced Multiple Unmanned Aerial Vehicle Swarm Formation Control Using a Novel Fractional Swarming Strategy Approach”, Fractal Fract, vol. 8, pp. 334, 2024, Available from: https://doi.org/10.3390/fractalfract8060334

[13] Chuanyue Wang, Lei Zhang, et.al, “A Cooperative Game Hybrid Optimization Algorithm Applied to UAV Inspection Path Planning in Urban Pipe Corridors”, Mathematics, vol. 11, pp. 3620, 2023, Available from: https://doi.org/10.3390/math11163620

[14] Zhenshi Zhang, Huan Liu, et.al, “A Dynamic Task Scheduling Method for Multiple UAVs Based on Contract Net Protocol”, Sensors, vol. 22, pp. 4486, 2022, Available from: https://doi.org/10.3390/s22124486

[15] Xiaohong Yan, Renwen Chen, et.al, “UAV Cluster Mission Planning Strategy for Area Coverage Tasks”, Sensors, vol. 23, pp. 9122, 2023, Available from: https://doi.org/10.3390/s23229122

[16] Daosen Zhai, Huan Li, et.al, “Joint position optimization, user association, and resource allocation for load balancing in UAV-assisted wireless networks”, Digital Communications and Networks, vol. 10, pp. 25–37, 2024, Available from: https://doi.org/10.1016/j.dcan.2022.03.011

[17] Franklin Salazar, Maria Sofia Martinez-Garcia, et.al, “Optimization of the solar energy storage capacity for a monitoring UAV”, Sustainable Futures, vol. 7, pp. 100146, 2024, Available from: https://doi.org/10.1016/j.sftr.2023.100146

[18] Tiseira, R. Novella, et.al, “Concept design and energy balance optimization of a hydrogen fuel cell helicopter for unmanned aerial vehicle and aero taxi applications”, Energy Conversion and Management, vol. 288, pp. 117101, 2023, Available from: https://doi.org/10.1016/j.enconman.2023.117101

[19] Yu-Hsuan Lin, Ming-Tsang Lee, et.al, “A thermal management control using particle swarm optimization for the hybrid electric energy system of electric vehicles”, Results in Engineering, vol. 21, pp. 101717, 2024, Available from: https://doi.org/10.1016/j.rineng.2023.101717

[20] Fei Xu, Shun Zi, et.al, “A computing offloading strategy for UAV based on improved bat algorithm”, Cognitive Robotics, vol. 3, pp. 265–283, 2023, Available from: https://doi.org/10.1016/j.cogr.2023.07.005

[21] Jian Sun, Zewen Li, et.al, “Hybrid power system with adaptive adjustment of weight coefficients multi-objective model predictive control”, Electrical Power and Energy Systems, vol. 153, pp. 109296, 2023, Available from: https://doi.org/10.1016/j.ijepes.2023.109296

[22] Huanhuan Hu, Shufen Gong, et.al, “Energy demand forecasting using convolutional neural network and modified war strategy optimization algorithm”, Heliyon, vol. 10, pp. e27353, 2024, Available from: DOI: 10.1016/j.heliyon.2024.e27353

[23] Ang Li, Mark Hansen, et.al, “Traffic management and resource allocation for UAV-based parcel delivery in low-altitude urban space”, Transportation Research Part C, vol. 143, pp. 03808, 2022, Available from: https://doi.org/10.1016/j.trc.2022.103808

[24] Muhammad Morshed Alam, Sangman Moh, “Joint topology control and routing in a UAV swarm for crowd surveillance”, Journal of Network and Computer Applications, vol. 204, pp. 103427, 2022, Available from: https://doi.org/10.1016/j.jnca.2022.103427

[25] Yuhang Han, Miaohan Zhang, et.al,” Two-stage heuristic algorithm for vehicle-drone collaborative delivery and pickup based on medical supplies resource allocation”, Journal of King Saud University - Computer and Information Sciences, vol. 35, pp. 101811, 2023, Available from: https://doi.org/10.1016/j.jksuci.2023.101811