Journal of Information Systems Engineering and Management
2025, 10(13s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Cluster based UAV Path Planning Using White Shark Optimizer (WSO) Algorithm for LoRaWAN

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ARTICLE INFO

Received: 30 Nov 2024

Revised: 12 Jan 2025

Accepted: 30 Jan 2025

ABSTRACT

Introduction: LoRaWAN defines the network architecture and communication protocol for Long-distance devices among Low-power Wide Area Network (LPWAN). Wide-ranging coverage and great mobility of Unmanned Aerial Vehicles (UAVs) provide up new possibilities for data collection. The main problem in UAV data collection is to tackle the path planning.

Objectives: The main objective of this work is to determine the UAV trajectory path to minimize the UAV flying distance and data gathering time.

Methods: An effective Cluster based UAV Path Planning (CPP) using White Shark Optimizer (WSO) algorithm is proposed. The proposed algorithm is based on distance among the cluster head (CH) and the UAV Data Collection Point (DCP), energy level of the nodes and sensor's data generation rate.

Results: By simulation results, it has been shown that CPP-WSO attains lesser data collection delay and packet drop rate with higher packet delivery ratio and average residual energy.

Conclusion: The proposed CPP-WSO enhances the lifetime of both sensor nodes as well as UAV.

Keywords: LoRaWAN, Unmanned Aerial Vehicle (UAV), Data collection, Clustering, Path planning, White Shark Optimizer (WSO).

INTRODUCTION

Long-range communication is made possible by the LoRa physical layer, whereas LoRaWAN defines the network architecture and communication protocol [1]. LoRaWAN involves nodes sending data to several gateways, which use different backhaul techniques to send it to a cloud-based network server. LoRaWAN can handle mobile nodes without requiring handovers between gateways, which makes it appropriate for IoT applications that are focused on asset tracking [2]. Wide-ranging coverage and great mobility of UAVs provide up new possibilities for IoT data collection. UAVs may gather data in close proximity to sensors, significantly lowering IoT energy consumption. IoT and UAV work together to enable efficient and timely data collection [3]. Due to its ability to optimise its trajectory, UAVs shorten the time needed to collect data [4]. Combining LoRaWAN and UAV technology provides a potent solution for autonomous operations, remote sensing, and data-driven decision-making in a variety of industries. [5][6].

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 [7] [8]. When we examine UAVs, the main problem to tackle is path planning. The optimisation path's primary goal is to locate a safe combat route that uses the least amount of energy while still enabling the UAV to complete its mission [9][10].

The major goal of this study is to determine the UAV trajectory path to minimize the UAV flying distance and data gatheing time. For this, an effective cluster based UAV path planning algorithm for LoRaWAN is proposed.

RELATED WORKS

The authors in [11] provide three cost factors that influence energy consumption: path security, length, and smoothness. They have presented a heuristic evolutionary method that maximises path development by combining evolutionary operations. In order to collect data in presence of UAVs attacks, Wang and Gursoy [12] investigated robust UAV path planning. They propose a reinforcement learning framework with high mission success and data collection rates for path planning under realistic limitations. In order to globally optimise UAV pathways while satisfying security and speed constraints, Bai et al. [13] presented a path planning solution based on A* and DWA. A system for gathering measured data from nodes using a drone and transmitting it to a base station using LoRaWAN, was proposed by Holtorf et al. [14]. Optimization strategies were proposed by Zhang et al. [15] to enhance UAV data gathering in LoRa networks. They introduced an enhanced Genetic Algorithm for trajectory planning that combines local search optimisation methods and Teaching-Learning-based Optimisation (TLBO) to accelerate path solution and convergence time.

PROPOSED METHODOLOGY

System Model

In this paper, effective cluster based UAV path planning algorithm for LoRaWAN is proposed. In system model, energy-limited IoT devices are placed in the network region. The network is divided into many clusters. A UAV is deployed in the initial location known as the takeoff-point. The cluster members in each cluster, transmit their gathered data to the CH to aggregate the data. The CHs mark the possible DCPs for the UAV. From the starting-point, the UAV visits each data collection point and communicate only with the CHs to finish the data gathering task.

The clustering algorithm is derived from the distance between the CHs and the UAV data collection point, energy level of the nodes and sensor's data rate.

Clustering Algorithm

The CH selection technique is based on ILEACH that considers the average distance between neighbouring nodes, the amount of leftover energy, and the distance among the CHs and the UAV starting-point. The following parameters are calculated.

The mean distance of neighbour nodes is calculated by

$$AD_i = 1/k(j) \quad (1)$$

where k(j) is the mean distance among all neighbour nodes of j inside the radius r_c and j, which is given by,

$$\square(\square) = \frac{\sum_{\square-\square\square(\square)} \square(\square,\square)}{\square_{\square}(\square)} \quad (2)$$

Ne(j) indicates the set of neighbor nodes of j. The average energy consumption then drops as this node communicates with the nearby nodes. k(j, i) denotes the distance among i and j.

The number of nodes covered factor (N_j) is given by,

$$\square_{\square} = 1 - \frac{1}{\square_{\square}(\square)} \quad (3)$$

where $N_u(j)$ denotes the nodes located in j within r_c. The cluster controlled by this node performs better in terms of coverage the greater $N_u(j)$.

The remaining energy E_j is computed as

$$E_j = e^{Er/\ Ei} \quad (4)$$

where E_r and E_i are the remaining energy and initial energy.

The distance from the node to the starting-point D_j is computed as

$$D_j = 1\ /\ d(j) \quad (5)$$

The following are the precise steps of the enhanced algorithm:

Step 1: Each node computes its delay, t(i), which is given by,

$$\square(\square) = \square \times \square^{-\square_{\square}} \quad (6)$$

Where $\square_{\square} = 100 \times [(\square_1.\square\square_{\square}) + (\square_2.\square_{\square}) + (\square_3.\square_{\square}) + (\square_4.\square_{\square})]$ (7)

Where β is the proportional coefficient used to determine delay size. δ_1, δ_2, δ_3, and δ_4 are the weights of the metrics and the sum of all these weights will be equal to 1.

Step 2: A Node i declares itself to be the CH and transmits notification to its neighbours, if it does not receive any notification from other CHs, within time tc(i).

Step 3: A node is considered as a member when the timer is over or if it receives the CH information.

Step 4: A node decides to join the latest cluster if it receives multiple CH notifications.

WSO Optimization Model

The goal of this section is to determine a UAV's shortest scheduled flight path. Beginning at the take-off point, the UAV travels through each DCP at a set height and speed before ending back at the staring-point.

The goal of the UAV path optimization is to minimise the flying distance F, which may be stated as follows:

$$\square = \square\square\square \sum_{\square \neq \square} \square_{\square\square} \square_{\square\square} \tag{8}$$

$$\square.\square. = \begin{cases} \sum_{\square=1}^{\square+1} \square_{\square\square} = 1; \square = 1 \ \square\square \ \square + 1 \\ \sum_{\square=1}^{\square+1} \square_{\square\square} = 1; \square = 1 \ \square\square \ \square + 1 \\ \sum_{\square=1}^{\square+1} \sum_{\square=1}^{\square+1} \square_{\square\square} = \square + 1; \square, \square \in \square \\ \square_{\square\square} \in \{0,1\}; \square, \square \in \square \end{cases} \tag{9}$$

where n indicates the number of the DCPs, i = 1 indicates the UAV staring-point, k_{ij} indicates the distance between i and j, and x_{ij} indicates the decision factor. It is assumed that i and j are the number of DCPs, such that i, j ∈ O, where O = {1, 2,..., n + 1}. x_{ij} = 1 when i ≠ j, and otherwise, it is 0. The constraint condition is represented by Eq. (9). The goal function must satisfy the conditions that stipulate that each DCP must be traversed once and that all DCPs must be included in any potential traversal sequence.

White Shark Optimizer (WSO) Algorithm

The WSO [17] is a real-time metaheuristic technique that can provide solution to various optimisation problems. This method mimics the behaviour of white sharks using their sense of smell and vision. The sharks can dynamically update their positions corresponding to the best solutions, to provide the required outputs. The position of a white shark is computed using Eq. (10):

$$\square = \begin{bmatrix} \square_1^1 & \square_2^1 & \cdots & \square_\square^1 \\ \square_1^2 & \square_2^2 & \cdots & \square_\square^2 \\ \vdots & \vdots & \ddots & \vdots \\ \square_1^\square & \square_2^\square & \cdots & \square_\square^\square \end{bmatrix} \tag{10}$$

where s_{ab} denotes the position of the ath shark corresponding to the ath dimension.

The velocity of a white shark is represented as:

$$\square_{\square+1}^{\square} = \square\left(\square_\square^\square + \square_1\left[\square_{\square\square\square\square\square\square_\square} - \square_\square^\square\right] \times \square_1 + \square_2\left[\square_{\square\square\square\square}^{\square\square} - \square_\square^\square\right] \times \square_2\right) \tag{11}$$

where $\square_{\square+1}^{\square}$ and $\square_\square^\square$ indicate the updated velocities of bth shark in iterations (m + 1) and m, respectively. p_1 and p_2 are the possibilities of sharks that monitor $\square_{\square\square\square\square\square\square_\square}$ and $\square_{\square\square\square\square}^{\square\square}$, which denote the best global positions at mth iteration, while $\square_\square^\square$ indicates the position of bth shark in iteration m. k_1 and k_2 are random constants. $\square_{\square\square\square\square}^{\square\square}$ denotes the bth best-defined position. α indicates the WSO constriction factor

The position update equation of the white shark is given by

$$\square_{\square+1}^{\square} = \begin{cases} \square_\square^\square \bullet \neg \oplus \square_\square + \square \bullet \square + \square \bullet \square & \square\square \ \square\square\square\square < \square\square \\ \square_\square^\square + \frac{\square_\square^\square}{\square} & \square\square \ \square\square\square\square \geq \square\square \end{cases} \tag{12}$$

where c and d indicate binary vectors, u and l indicate the upper and lower ranges of the searching space, ¬ indicates the negative operator, w_o and f indicate a logical vector and the wavy motion frequency of white shark. The direction in which one is moving in search of the best shark is:

$$\acute{\square}_{\square+1}^{\square} = \square_{\square\square\square\square\square\square_\square} + \square_1 \vec{\square}_\square \times \square\square\square(\square_2 - 0.5) \quad \square\square \ \square_3 < \square_\square \tag{13}$$

where $\acute{\square}_{\square+1}^{\square}$ is the updated position of the ith shark, and y_1, y_2, and y_3 are random values ranging [0, 1]. (y_2 – 0.5) can alter the search direction since it gives 1 or −1. The white shark's smell intensity is indicated by Z_z, while the distance among the prey and the shark is shown by $\vec{\square}_\square$.

EXPERIMENTAL RESULTS

The proposed CPP-WSO algorithm is implemented in NS3. The experimental parameters are given in Table 1.

Number of Nodes	20,40,60,80,100
Topology size	50 m * 50 m
MAC protocol	LoRaWAN

Source of Traffic	CBR
Number of data Flows	6
Data sending Rate	50 KB/s
Input Energy	25 Joules
Transmitting power	0.8 Watts
Receiving power	0.3 Watts
Speed of UAV	20-40 m/s

Table 1 Experimental parameters

RESULTS

The CPP-WSO algorithm's performance is compared to the Improved genetic algorithm based on TLBO (TGA) [15], in terms of data collection delay, packet delivery ratio, packet drop and average residual energy metrics. The number of sensors transmitting data to the UAV is varied from 20 to 100.

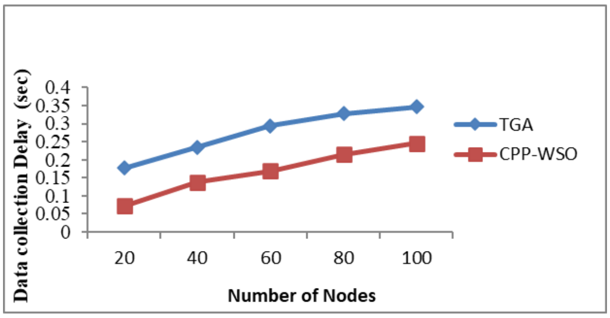

Figure 3 Data Collection Delay for sensors

From figure 3, it can be seen that the data collection delay of CPP-WSO is 41% lesser than TGA.

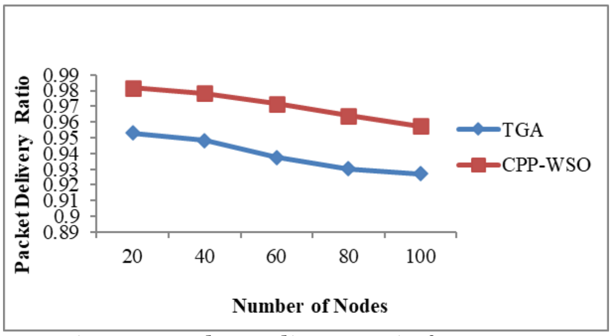

Figure 4 Packet Delivery Ratio for sensors

From figure 4, it can be seen that the packet delivery ratio of CPP-WSO is 3% higher than TGA.

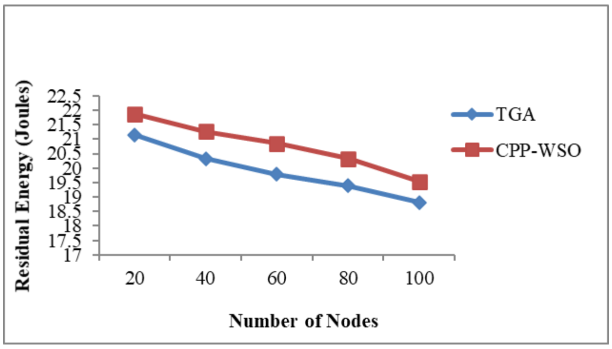

Figure 5 Residual Energy for sensors

From figure 5, it can be seen that the residual energy of CPP-WSO is 4% higher than TGA.

CONCLUSION

In this paper,, an effective cluster based UAV path planning using WSO algorithm is proposed. The CPP-WSO algorithm is simulated in NS3 and its performance has been compared with the TGA algorithm. By experimental results, it has been shown that CPP-WSO attains lesser data collection delay and packet drop rate with higher packet delivery ratio and residual energy.

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