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Trajectory optimization in large scale UAV-assisted WSNs

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***Abstract*— Monitoring systems based on Wireless Sensor Networks (WSNs) have received rapid development in the past few years. A major problems with large sensor networks composed of tens of thousands of sensors, computing, and communication modules are related to the complexity of network management and the reliability of the sensor data exchange and processing.**

At the same time, unmanned aerial vehicles (UAVs) have a key role in the development of communications due to their mobility, ability to be rapidly deployed and the relatively easy data exchange with ground wireless devices. The UAVs role as communication gateways and data concentrator in a hybrid WSNs can simplify drastically the sensor data routing protocols, data collection and the process analysis.

This research presents an optimization method for trajectory planning in a single UAV-assisted hybrid wireless sensor network.

The main contribution of the study is to create an adaptive UAV trajectory optimization method based on optimized number of contact points to collect data from ground wireless sensors with the aim of avoiding blocked regions, passing near predefined control points, and guaranteeing time for air-to-ground (A2G) communication with each sensor module, and minimizing the total path length and the WSN total energy consumption.

***Keywords*—A2G, trajectory optimization, UAV, WSN, Wireless Sensor Networks.**

I. INTRODUCTION

Wireless sensor networks (WSNs), composed of thousands of sensing, computing and communication nodes, are used in all areas of industry and the environmental monitoring and management. The integration of joint UAV-WSN systems leads to the expansion of surveillance areas, significant performance improvement and dramatic life-span of autonomous battery-powered sensor modules located in hard-to-reach or life-threatening locations.

The ability of a UAV to crawl and directly collect sensor data from ground sensor modules with subsequent storage and processing greatly simplifies the sensor data routing protocols and reduces the energy required for the sensor module to relay and route data from neighboring sensor modules[1].

At the same time the large scale UAV-assisted WSNs are much more adaptive and configurable if there is a need of ground sensor modules position’s changes which is typical for mobile ad-hock WSNs.

II. RELATED WORKS

The authors of the study [2] considered different data acquisition algorithms in order to take into account the duration of the stay at the contact point and the transmission rate between the UAV and the sensor modules. The use of UAVs to collect data from dispersed mobile sensors distributed along a predetermined linear path where each has a different speed is investigated.

In [3], the authors consider a clustering method in UAV-assisted WSNs, where the UAV can fly to a sensor node to collect data and then broadcast the collected data to a predefined gateway control center.

In [4], the paper presents a WSN with an integrated UAV that is used to collect data from a group of sensor nodes, with an algorithm to maximize the average data collection rate of all sensor nodes. The research examines communication planning with this UAV and three-dimensional (3D) trajectory formation.

The authors of the study [5] optimize the grouping of ground sensors in clusters, and solve an optimization problem of defining the trajectory between them in order to shorten the flight time.

In [6], optimization techniques are applied to improve the coverage ratio of UAV based data concentrator and ground sensor modules by increasing the wireless transmission power.

In [7],[8] are presented techniques to improve energy efficiency in UAV-based Mobile Edge Computing (MEC) systems. In these research works, the authors tried to solve an optimization problem related to MEC systems, such as energy consumption and coverage.

In [9], a mixed-integer linear program (MILP) was formulated to minimize the total distance traveled by a UAV while collecting data from scattered ground sensors.

In [10], the authors propose a genetic algorithm to find the shortest path for a group of UAVs, with the aim of simultaneously collecting data from multiple ground sensor modules.

In [11], the study presents a Q-Learning-based path planning algorithm for UAVs with the function of autonomously navigating between contact points in a defined area while avoiding obstacles or restricted areas.

A deep strategy based on Q-net is used to solve the multi-

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objective optimization problem with the objectives: to reduce latency and energy consumption in [12].

An extended heuristic algorithm is proposed by the authors in [13] to optimize objectives, minimize energy consumption, and reduce delay for task execution.

In [14] the authors propose optimized UAV-assisted communication systems, with a solution based on fuzzy logic to improve the coverage factor.

In [15] and [16], the authors present a Q-learning algorithm to solve the autonomous UAV planning problem. Q-learning was also used to select trajectories while avoiding obstacles.

In [17]. the authors use a modeled environment with limited 2D space for UAV action. This reduces the effectiveness of UAVs when operating in real-world environments, where as these studies ignore the challenges associated with limited battery constraints.

Most of the developed optimization models described above are limited to 2D navigation space (i.e., fixed altitude), where the UAV cannot change its altitude to cross obstacles.

III. TRAJECTORY OPTIMIZATION PROBLEM FORMULATION

Correct problem formulation is a key requirement for successful implementation of every optimization method. In this paper, the problem is defined as a multi-criteria optimization problem and the objectives are to minimize the energy consumed by the components of the large wireless sensor network containing thousands of ground wireless sensor modules using UAV based mobile data concentrators. The UAV-assisted WSN system considered in this paper consists of a single UAV playing the role of a mobile wireless data concentrator and multiple ground-based wireless sensor modules communicating during fixed time windows with this UAV only in line-of-sight (LoS) mode.

The number of sensor modules operating in active mode as part of a WSN is defined as

N = {1,2,3,…….n}

In each wireless sensor module, processes of measurement, processing and subsequent sending of the processed sensor data to the UAV based mobile data concentrator are carried out when the latter is in the direct line of sight (LoS) with air to ground type communication (A2G).

The next key parameter is the location of the wireless sensor module SM_i, defined by its GPS coordinates X_i, Y_i and Z_i.

Although all sensor modules are ground-based, the altitude Z value of the sensor module plays an important role in the optimization process. Due to the peculiarities of the terrain, this parameter varies widely and has a significant impact on the 3D trajectory of the UAV data concentrator.

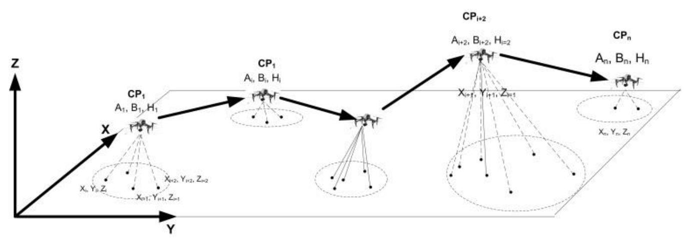
The present study is based on a quad copter-type UAV, equipped with wireless communication module and data storage. The UAVs flying control system has the ability to hover over a certain contact point (CP) in communication the range of one or more ground-based sensor modules for fixed time to exchange of sensor data.

The number and coordinates of the hinge and contact points for the purpose of sensor data exchange is unknown and subject to optimization.

For this reason, we define the variable

CP = [1,2,3,…..s] defining the number of points of contact with one or a group of ground sensor modules.

The 3D trajectory optimization based on the CP, N and SM_i, give additional benefits in the UAV-assisted WSNs by increasing the total energy efficiency illustrated on figure 1 bellow:



Фиг1 Typical UAV-assisted 3D trajectory optimization

The following equation defines the distance between the *j*th hover point of the UAV data concentrator with coordinates A_j, B_j and H_j and the coordinates of the *i*-th sensor module.

$$l_{ij} = \sqrt{(A_j - X_i)^2 - \left(B_j - Y_i\right)^2 + \left(H_j - Z_i\right)^2} \quad (1)$$

The variable K_{ij} represents the line-of-sight (LoS) availability between the i^{th} ground sensor module and the j^{th} contact point of the UAV data concentrator. K_{ij} is subject to two restrictions specified in formulas 2 and 3.

$$\text{Constraint1:} \quad K_{ij} = \begin{cases} 1, & if\ j = argmin_{j \in CP}\ l_{ij} \\ 0, & otherwise \end{cases} \quad (2)$$

K_{ij} =1 illustrates an existing LoS and communication link establishment.

K_{ij} =0 gives that there is no LoS or the area is forbidden or blocked and no communication link can be established.

This constrain is defined by predefined circle zones by gps coordinates of the center and radius.

$$\text{Constraint2:} \quad \sum_{j=1}^{CP} K_{ij} = 1, i \in N \quad (3)$$

The WSN UAV-assisted data concentrator storage has a data capacity limitations and can serve up to NL number of sensor modules at every data collection tour.

$$\text{Constraint3:} \quad \sum_{j=1}^{CP} K_{ij} \leq NL, i \in N \quad (4)$$

The bandwidth speed BS of the specific communication data exchange from the i^{th} ground sensor module to the UAV data concentrator at a connection point j is presented by the following equation:

$$BS_{ij} = S\ log_2\left(1 + \frac{tp_i^t\ cp_{ij}}{\sigma^2}\right) \quad (5)$$

Where:

- S parameter denotes the total system bandwidth;
- tp_i^t represented the transmission power;
- cp_{ij} represented the channel power gain;
- σ^2 represented the white Gaussian noise

The time needed by the i^{th} sensor module to transmit F_i number of sensor data packages to the UAV at j^{th} contact point is the following:

$$T_{ij}^F = \frac{F_i}{BS_{ij}} \quad (6)$$

The amount of energy E consumed of a i^{th} sensor module at j^{th} contact point is calculated by:

$$E_{ij}^t = tp_i^t T_{ij}^F = \frac{F_i tp_i^t}{BS_{ij}} \quad (7)$$

Based on the equations above the total energy consumption spend by all sensor modules included in the trajectory tour of the UAV concentrator is:

$$E_{total} =: \sum_{i=1}^{t}\sum_{j=1}^{s} K_{ij}\ E_{ij}^t \quad (8)$$

The summarized trajectory optimization problem formulation in WSN assisted by single UAV is the following:

$$\min [A_j, B_j, H_j,\ NL_{WSN}, E_{total},]\mathrm{CP} \quad (9)$$

Subject to:

Constraint1: $K_{ij} \in \{0,1\}$

Constraint2: $\sum_{j=1}^{CP} K_{ij} = 1,\ i\ \in N$

Constraint3: $\sum_{j=1}^{CP} K_{ij} \leq NL, i\ \in N$

Constraint4: $\sum_{i=1}^{t}\sum_{j=1}^{s} K_{ij}\ E_{ij}^t$

Constraint5: $X_{min} \leq A_j \leq X_{max}$

Constraint6: $Y_{min} \leq B_j \leq Y_{max}$

Constraint7: $Z_{min} + 10m \leq H_j \leq Z_{max} + 30m$

Where the UAV 's contact point position's location coordinate set $\{(A_j, B_j, H_j)\}$ and the number of the contact point positions CP to be optimized

IV. Proposed method

The multi-criteria optimization problem is presented in equation (9) for UAV-assisted WSN.

Because the number of the connection points (CP) and their locations is unknown and depends of the UAV's data capacity and UAV's flight energy consumption is not suitable to be used the traditional gradient descent and similar methods for optimization.

The proposed method solving the optimization problem described above is differential evolution-based [18] with additional extension using fuzzi-based control parameters adaptation [19][20].

The presented combination of differential evolution method and fussy logic is a heuristic approach for global optimization of non-linear and non-differentiable continuous spatial functions.

Similar to other direct search methods, such as genetic algorithms and evolutionary strategies, the differential evolution algorithm starts with an initial population of candidate solutions. These candidate solutions are iteratively improved by introducing mutations into the population and retaining the most suitable candidate solutions that yield a lower objective function value.

A significant advantage of this method is that it is suitable for handling non-linear and non-differentiable multidimensional objective functions, while requiring very few control parameters to control the minimization.

As is shown on Figure 2 bellow the variable population is generated randomly and try to be optimized adaptively in the limit of the pre-specified limitations.

The optimization process starts with the number of the contact points which by default is unknown. Therefore we assume in the beginning of the optimization process that the number of the contact points is equal to the number of the sensor modules and is based on their 2D coordinates X and Y.

The parameter H which presents the height of the UAV's contact point is part of the optimization process and as is shown in Constrain 7. This parameter varies in distance

10m to 50m above current Z_i coordinate of the sensor module as is shown in constrain7.

The value of this A2G communication parameter depends of the distance between neighbour sensor modules and the value of the K_{ij} LoS constrain.

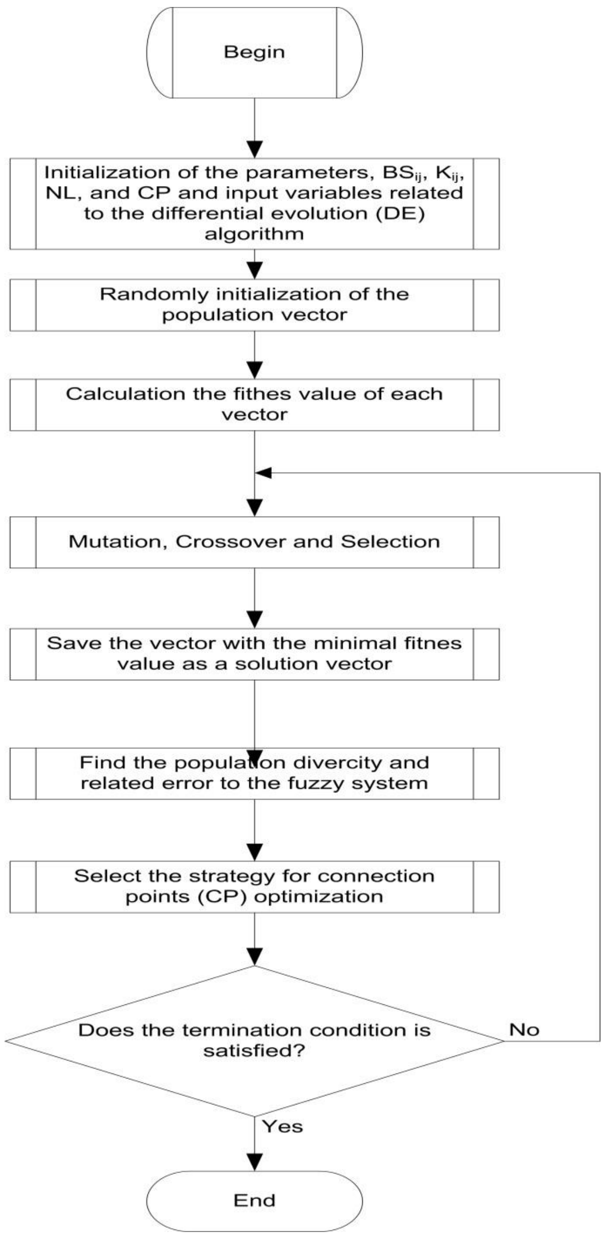


Fig. 2 Method for differential evaluation and fussy logic optimization

The presented method is tested successfully in experimental conditions, based on quad copter model 4DRC-F3 equiped with LoRA E220-900T220 communication module and 5 mobile wireless battery powered ground sensors, situated on different distances.

V. Conclusion

In the present research work, an optimization problem in a wireless sensor network assisted by a single UAV data concentrator is considered. The goal of this multicriteria optimization is to minimize the consumed energy by optimizing the GPS coordinates of the contact points from which data is exchanged between a single UAV data concentrator and one or several sensor modules.

To solve this problem, a method and algorithm based on differential evolution and fuzzy logic is proposed.

Since the number of contact points is considered unknown in the initial optimization process, it is assumed to be equal to the number of sensor modules.

Based on strategies for generating sample vectors and iteratively changing them in the optimization process, GPS coordinates of height-optimized and location-optimized contact points are generated, enabling A2G exchange of sensor data in LoS conditions with more than one sensor module at the same time, which can significantly reduce the number of contact points and the amount of energy required by the UAV hub and sensor modules in the communication process.

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