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Energy Efficient Wireless Data Gathering using Unmanned Aerial Vehicle by adopting Crow Search Optimization Algorithm

V. Thiyagarajan[1*]

[1]*Assistant Professor, Department of Electronics and Communication Engineering, Arunai Engineering College, Tiruvannamalai, Tamilnadu. India*

[*]Corresponding author email: thiyagasbc@gmail.com

Abstract: Nowadays, data gathering from wireless sensors using unmanned aerial vehicles has been a topic of interest. In this manuscript propose an energy efficient solution for unmanned aerial vehicles that diminish the energy consumption of sensors while accomplishing a tour in spatial distributed wireless sensors that are collected. The goal of the proposed method of energy efficient Wireless Data gathering Using Unmanned Aerial Vehicles by adopting Crow Search Optimization (WDG-UAO-CSO) for determining the UAV position 'stops' in the data collected from the sensor subset placed at similar neighborhood and get the route in the data gathering tour on energy efficient way. First, formulate the non-convex optimization issue and minimum complexity system is iteratively achieved, an optimal cub solution. At last the execution is performed on network simulator 2 software. The experimental outcome portrays the better result in communication and flight energies consumption compared to exiting method such as WDG-UAV-TPO (travel path optimization). The proposed method energy efficient WDG-UAV-CSO produces 96.66% better than existing energy efficient WDG-UAV-TPO respectively.

Keywords: wireless sensors, unmanned aerial vehicle, optimal solution, crow search optimization algorithm.

1. INTRODUCTION

The uses of unmanned aerial vehicles (UAV) are the rapid wireless communication platform which has received by the recent significant attention [1]. On this way unmanned aerial vehicles are used by the wireless communicates for improve the attention of ground wireless device and connectivity [2, 3]. In unmanned aerial vehicles act as the base station of the mobile aerial that provides the dependable downlink and uplink communication for the wireless network capacity of ground users [4]. Compared to the terrestrial base station using unmanned aerial vehicles based aerial base station is to provide the on the fly communication ability [5]. Also the high elevation unmanned aerial vehicles enables them to establish line of sight (LoS) communication link is effectively and justifying the signal in blockage and shadowing [6]. Due to the altitude and mobility is adjustable in unmanned aerial vehicles, in unmanned aerial vehicles move towards the possible ground users and establish the low transmit power in reliable connections. Hereafter cost-effective and energy-efficient solution is providing the data collection of land mobile users is spread over the geographic area with limited land infrastructure [7, 8]. Certainly, the internet of things plays a key role in UAVs, which is collected on battery-limited devices like sensors and health monitors [9]. Such devices cannot transmit the energy constraints over long distances. In such unmanned aerial vehicles they can energetically move towards the scenarios in IoT devices. In the communication range of the transmitter, the IoT data is collected and transmitted to the other devices. [10, 11]. In this case unmanned aerial vehicles play a role in base station for IoT network in moving aggregators are several challenges are addressed in the optimal development, mobility and energy efficient use of unmanned aerial vehicles [12, 13].

In this manuscript, investigate the moment and optimal development in downlink wireless communication which is supported for the single unmanned aerial vehicles. In this work proposed a crow search optimization algorithm for optimal development of multiple unmanned aerial vehicles delivers the attention of ground users. This provides the downlink coverage analysis of network in unmanned aerial vehicles in finite number of ground users. The major contribution of this manuscript are summarized below,

- In this manuscript, Energy Efficient WDG-UAV-CSO [14] is proposed.
- In this design an outline of energy efficient data collection as WSN with unmanned aerial vehicles.
- The proposed method takes the total energy consumption of the UAV route to travel and data collection assuming the communication speed among sensors and UAV.
- After that express the crow search optimization to determine the stop position of UAV.
- Based on the complexity and non-convexity issue derive a suboptimal and then deterministic solution depending on decomposition issue and proposes a process for solving every sub-problem individually.
- Then, the simulation result shows the performance of proposed system and compares the previous method based on TSP-N method, which optimizes the UAV travel route through the sensors in the region.
- When the simulation is performed on network simulator 2 software and the proposed system is compared with existing methods energy efficient WDG-UAV-TPO.

The remaining segment of this manuscript is designed as. Segment 2 delineates the literature survey. Segment 3 explains the proposed energy efficient WDG-UAV-CSO, Segment 4 demonstrates the results and discussion. Finally, Segment 5 concludes the manuscript.

2. LITERATURE REVIEW

Among the numerous researches work on energy efficient WDG-UAV some of the most recent works of research scholars were reviewed here in this section.

In 2019, Vladuta et al [15] have presented the optimization of data gathering on wireless sensor networks with UAV. To reduce transmission time and energy consumption in wireless sensors with limited capability. The optimization depends on the dynamic construction of route in UAV to gather the wireless sensors. Based on sensor location, groupings and optimization are performed for obtaining the best route for sensor locations. The simulation process is performed on network simulator 2 platform.

In 2017, Sharma et al [16] have presented the recovery of energy efficient devices for reliable communication on 5G-based IoT with UAV. In this energy efficiency method, the IoT based on 5G and BSNs are presented with multiple UAVs. The main profits reached with power consumption, end-to-end delay, and packet loss are able to provide energy efficient device discovery using 78.4% reduction on power consumption compared with existing algorithm. The main benefit of UAVs at energy efficient networks is proved by the numeric analysis that recommends 75% improvement on energy asymptote of existing network.

In 2020Poornima et.al in [17] have presented the online locally weighted projection regression (OLWPR) for anomaly detection of WSN. The OLWPR systems are not parametric, which utilize the data subset. Therefore, the complexity of calculation was reduced the WSN requirements. The dimensional reduction on LWPR was performed online using PCA to deal redundant and irrelevant data at input. The OLWPR arrives a detection rate 86 percent and minimum error rate 16%.

In 2017 Wang et.al in [18] have presented an innovative IDS named hierarchical spatial-temporal features-based intrusion detection system (HAST-IDS) that initially studies minimum-level spatial characteristics of network traffic with deep convolutional neural networks (CNN). The automatically learned traffic characteristics efficiently diminish FAR. The experimental outcomes show that superior performance of HAST-IDS.

In 2017Aditham et.al in [19] has presented the innovation system architecture, that internal attacks may be detected with data replication across multiple system nodes. The introduced system utilizes two-step attack detection algorithm as well as safe communication protocol for analyzing the processes running on system. An initial step contains building control instruction sequences for every process on system. The second stage contains matching such sequences of instructions between replica nodes. The experimental results show testing of hadoop and spark in real world with 20 percent code for analyzing program and incurring a 3.28 percent overhead time.

In 2018 Kurt et.al in [20] have presented a robust online detection algorithm for interference attacks and spurious data injection gives online estimates of recovered state. To assume the smartest attackers who were able to engineer stealth attacks to avoid detection or enlarge the detection delay of robust online detection algorithm. The numerical studies demonstrate that rapid and dependable response of

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system's detection mechanisms next to hybrid and stealth cyber-attacks.

In 2018 Kim et.al in [21] has presented a new structure of android malware detection. Its structure utilizes a variety of types of characteristics for reflecting the properties of Android applications as several features. A multimodal deep learning method was employed for detecting malware detection model. This manuscript was initial study of multimode deep learning method employed for detecting malware on Android. For estimating the yield, several experiments were taken with a total of 41,260 samples.

3. PROPOSED METHOD FOR ENERGY EFFICIENT WDG WITH UAV

The energy efficiency of wireless data collection is the optimization of UAV for data collection. Within the framework of energy efficient data collection is the design of WSN with flying UAV. To determine the optimization problem of UAV in stop position, the sensor will send the data in every stop with minimum energy consumption in data collection by availability requirements. When the unmanned aerial vehicle stops, the location of the selected sensors and if formulated as the clustering issue and stop location are determined by objective function of the linear relaxation of the route between the crow search optimization algorithms. In this, the energy-efficient WDG-UAV optimizes the route of UAV through the neighborhoods of sensors. The energy efficient wireless data collection with UAV is shown on figure 1.

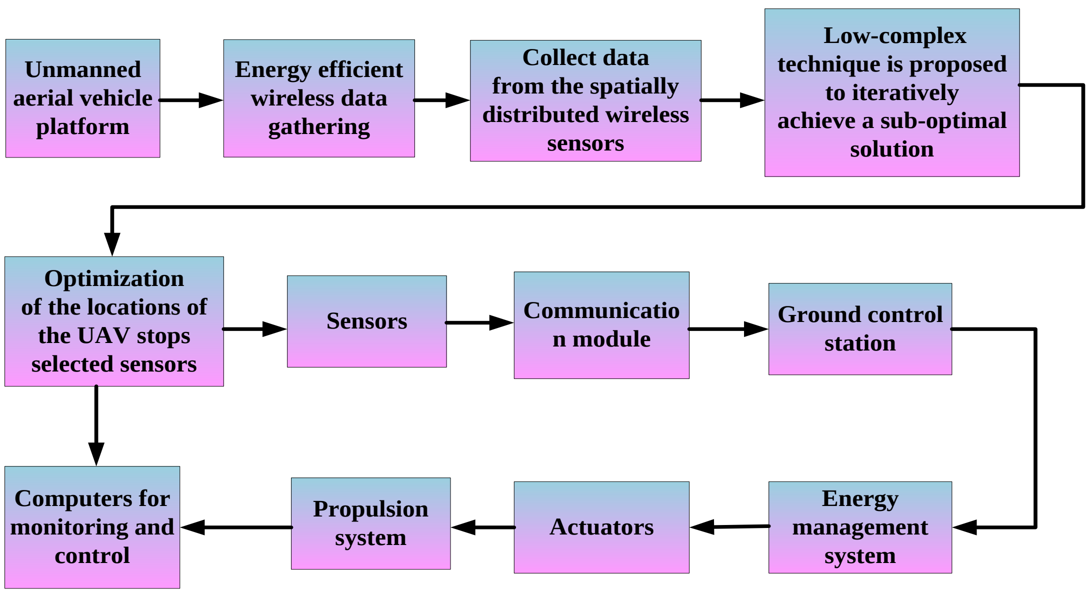

Figure 1: Block diagram for Energy Efficient WDG with UAV

In efficiently optimizing the drone's trajectory plane; the overall channel transmission time is compared in coherence time. Hence the system performance is focused on the average measurements rather than the instant ones which are possible on larger drone flight time compared to channel coherence time, which is measured at milliseconds. Thus the great-scale path loss is considering that result on channel gain.

Then, average data rate of communication among sensors R is located in drone position and A is represented by $S(R,A)$ is expressed in equation (1)

$$A(R,A) = Y\log_2\left(1+\frac{Q_T}{QK_{X-H}(R,A)M_0}\right) \quad (1)$$

where $QK_{X-H}(R,A)$ represents the path loss of average channel and deem the probabilistic path loss model on ground. The average path loss among sensors R and unmanned aerial vehicle located at the position A is represented as given below,

$$QK_{X-H}(R,A) = p_l(R,A)P_{LM}(R,A)+[1-p_l(r,a)]P_{LN}(R,A) \quad (2)$$

where $p_l(R,A)$ implies that LoS probability among sensors R and position of drone is A. Then the environment and elevation angle depends on the environment is shown in equation (3) and it can be described as below,

$$p_l(R,A) = \frac{1}{1+\alpha\exp(-\beta[\theta(r,a)-\alpha])} \quad (3)$$

where $\theta(R,A)$ represents the drone elevation angle in the position A with the sensors regards to R. When α and β

are the parameters depends on environment. In urban environment characteristics that are derived in the empirical method. Finally $p_l(R,A)$ and $p_{lN}(R,A)$ are the LoS and non-line-of-sight (NLoS) environments in average path loss are described below,

$$PL(R,A) = 10\eta \log_{10}\left(\frac{4\pi e_d}{d}\,||R-A||_2\right) + \xi LoS \tag{4}$$

$$PL_N(R,A) = 10\eta \log_{10}\left(\frac{4\pi e_d}{d}\,||R-A||_2\right) + \xi NLoS \tag{5}$$

where the $PL(R,A)$ represents the path loss in free space with η the path loss exponent, e_d denotes the frequency carrier, d denotes the light celerity, and $||R-A||_2$ represents the Euclidian distance separate the locations of R and A.

The drone model, power consumption of data collection excursion is two major classes that are flight and communication modes. When flight modes contain two modes in consumed power that are ensuring as obtainable motion. Then power is described as drone mass function is n_{twt} radius and count of propellers in s_q and m_q separately.

$$Q_{gwu} = \sqrt{\frac{(n_{twt}h)^3}{2\pi s_q^2 m_q \rho}} \tag{6}$$

where h and ρ denotes the gravity of earth and density of air. The transition of movement power position is deemed to drone speed linear function u_C can be expressed in below equation.

$$Q_{ts} = \frac{Q_e - Q_r}{u_{\max}} u_C + Q_r \tag{7}$$

where $u_{\max}$ represents the maximum speed of drone. Q_e And Q_s is the power level of the hardware.

In communication mode, the drone is deemed in fixed hover position. Therefore, the signal processing and communications power made up the hovering of consumed power. When the drone tour moving around number of positions and it can be expressed as $\{A_1,\ldots,A_M\}$, to optimize the positions and transfer the data in each sensor.

In this a_d, l indicating the variables in subset of sensors and it transfer the data to drone in the collection stop. $b_{d,d'}$ Represents the index variable for the unmanned aerial vehicle route, then the objective is calculated and weighted sum of energy is composed using drone in dissimilar sensors in data collection is expressed as below,

$$O = F_C + \sum_{L=1}^{L} \rho_L F_{R_L}$$

(8)

where F_D denotes the drone energy consumed during the data collection is written as equation (9)

$$F_C = \sum_{d=1}^{M}\sum_{l=1}^{L} a_{d,l} F_{d,l}^{stop} + \sum_{d=0}^{M}\sum_{d\neq 0}^{M} b_d F_d^{flight} \tag{9}$$

where F_d^{flight} represents the energy consumption of flying location A_d to another $A_{d'}$ expressed as below,

$$F_{d,d'}^{flight} = (Q_h + Q_{ts}) \times T_d^{flight} = \frac{(Q_h + Q_{ts})\,||(A_d - A_{d'}\,||_2}{u_C} \tag{10}$$

where $F_{d,d'}^{flight} = ||A_d - A_{d'}\,||_2 / u_C$ representing the trip time of drone from the position A_d to $A_{d'}$ and u_C denotes the speed of the drone, otherwise $F_{d,l}^{stop}$ is energy consumed by the data collecting the drone of the sensor R_l at the stop A_d can be expressed as,

$$F_{d,l'}^{stop} = (Q_h + Q_c) \times T_{l,d}^{c} = \frac{N_l(Q_h + Q_c)}{(S(R_l, A_d))} \tag{11}$$

where $T_{l,d}^{c} = N_l / (S(R_l, A_c))$ corresponds to time required for allocating the sensor data R_l in drone position A_d.

3.3 Step by step process of energy efficient WDG-UAV-CSO

In this section, the step by step procedure of Energy Efficient WDG-UAV-CSO is deliberated and the flow chat is given in figure 3.

Step 1: Initialization

To initialize original population by using crow search algorithm with determined number of iteration, sub carrier mapping M^q, transmitted signal $y^q(r)$, cyclic prefix Z_{cr}, received signal $p(r)$, detected signal $\hat{l}^u(r)$ and Energy Efficient Wireless Data Gathering

Step 2: Initialize Position and Memory of Crow

K numbers of crows are randomly positioned in an n-dimensional search space. The memory of every crow is initialized. Crows have hidden their foods in initial position.

Step 3: Random Generation

The parameters of localized with Energy Efficient WDG-UAV is randomly generated with the help of crow search optimization algorithm.

Step 4: To Evaluate Fitness Function

To select the Localized in Energy Efficient WDG-UAV-CSO approach is given in equation (11).

Step 5: Creation of New Position

Crow *s* wants to create a new position, for this purpose it approximately chooses the flock crows (t). Then crow *s* monitors the selected crow to determine the food position hidden through this crow. This procedure is repeated for all the crows. The new position of crow is given by,

$$X^{s,iter+1} = \begin{cases} X^{s,iter} + m_s \times fl^{iter} \times (r^{t,iter} - X^{s,iter}) & m_t \geq AP^{t,iter} \\ random\ \ position & otherwise \end{cases} \qquad (12)$$

$AP^{t,iter}$ Indicates that awareness of crow probability t at iteration

Step 6: To check feasibility

To check the feasibility of novel location of every crow, after checking feasibility, if the crow is feasible in new position, then it upgrades their location. If the crow is not viable in new position, then the crows stays in the initial position.

Step 7: Termination

After reaching best solution stop the process otherwise steps 5 to 7 are repeated until the criteria are met. At last the output of algorithm gives energy efficient WDG-UAV-CSO.

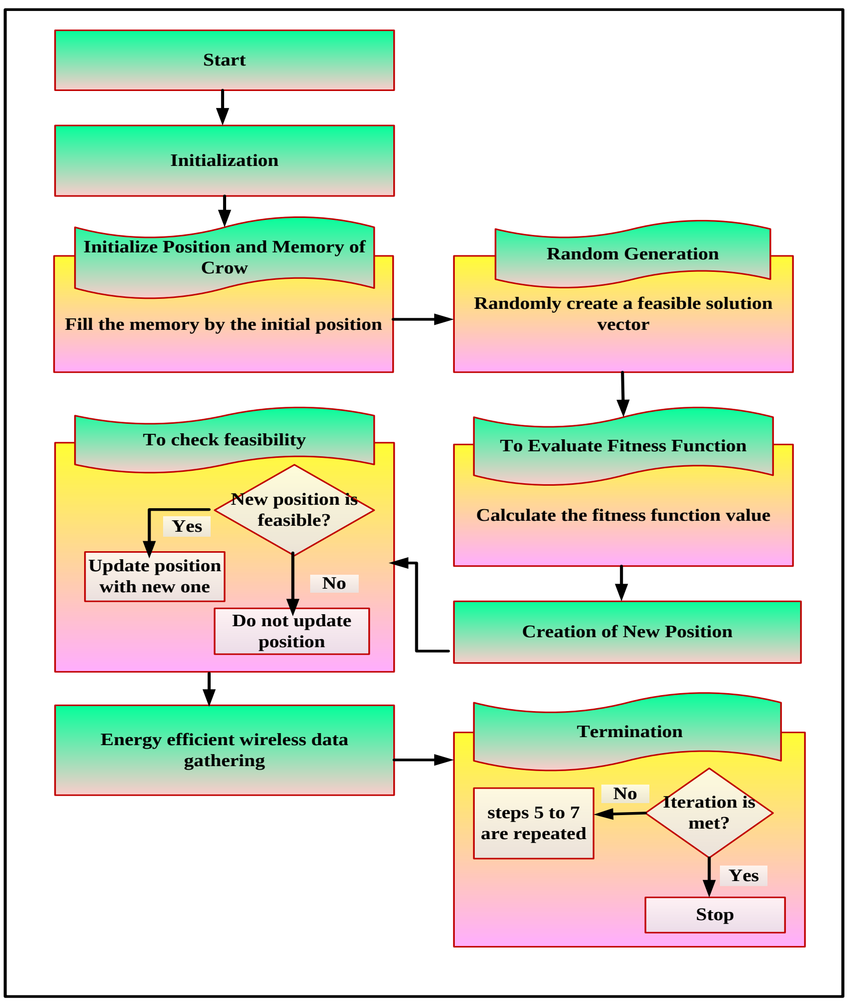

Figure 2: Flow chart for Energy Efficient WDG-UAV-CSO

4. RESULT AND DISCUSSION

In this section, the performance of energy efficient WDG-UAV-CSO is proposed. In this each sensor the neighborhood area is defined. UAV may obtain the sensor data reliably on region characterized. The major purpose of the proposed method is optimizing the path of the unmanned aerial vehicle in neighboring region that transmits the flies in general in the sensor region. Also this solution affects the position of UAV data rate and therefore the time required for completing the transmission. Furthermore, the discretization of environment requires a worldwide solution. Then the simulation is conducted on Network Simulator 2 (NS-2), version 2.34 is employed. Here the efficiency of proposed energy efficient WDG-UAV-CSO and compared with energy efficient WDG-UAV-TPO [22] approach. The simulation parameter of the proposed method displays on table 1.

Table 1: Simulation parameter

Parameter	Value
Bounded area of size	1x1 km^2
Software	(NS-2)
Sensors	Static
Transmission power	0.5 watts
Carrier sensing range	150 meters
Distribution area	2500 meters x 2500 meters

4.1 Simulation result of the proposed Energy Efficient Wireless Data Gathering with unmanned aerial vehicle using crow search optimization algorithm

From figures 3 to 6 portray that simulation result for energy efficient WDG-UAV. In this segment, various performances are calculated such as energy consumption based on count of sensors, energy consumption based on count of stops, energy consumption based on obtainable sensor energy and UAV altitude based on LoS and NLoS path variation are discussed. The performance of the proposed energy efficiency WDG-UAV-CSO method is analyzed and compared with existing method like energy efficient WDG-UAV-TPO.

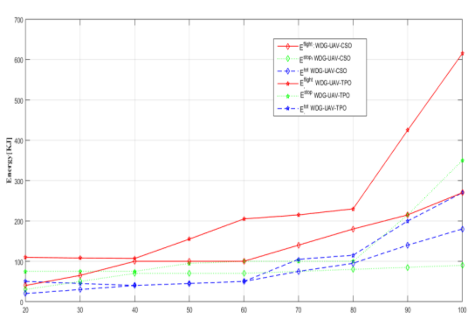

Figure 3: Energy consumption as number of sensors

From figure 3 shows the energy consumption function in various numbers of sensors. In this from, the proposed method energy efficient WDG-UAV-CSO produces 28.61% lower than existing energy efficient WDG-UAV-TPO in E^{flight} (WDG-UAV-CSO) method. The proposed method energy efficient WDG-UAV-CSO produces 37.80% lower than existing energy efficient WDG-UAV-TPO in E^{stop} (WDG-UAV-CSO) method. The proposed method energy efficient WDG-UAV-CSO produces 26.01% lower than existing energy efficient WDG-UAV-TPO in E^{tot} (WDG-UAV-CSO) method respectively.

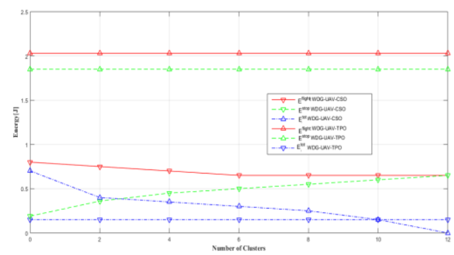

Figure 4: Energy consumption as number of stops

From figure 4 portrays that energy consumption as a function in various number of stop. In this figure the proposed method energy efficient WDG-UAV-CSO produces 37.45% lower than existing energy efficient WDG-UAV-TPO in E^{flight} (WDG-UAV-CSO) method. The proposed method energy efficient WDG-UAV-CSO produces 21.86% lower than existing energy efficient WDG-UAV-TPO in E^{stop} (WDG-UAV-CSO) method. The proposed method energy efficient WDG-UAV-CSO produces 49.83% lower than existing energy efficient WDG-UAV-TPO in E^{tot} (WDG-UAV-CSO) method respectively.

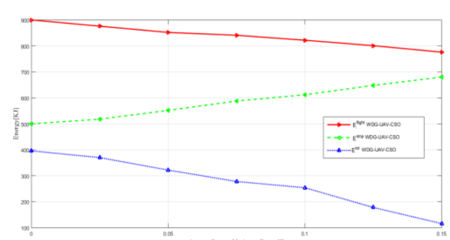

Figure 5: Energy consumption as sensors available energy

Figure 5 shows that the energy consumption functions in various sensors in obtainable energy. The proposed method E^{flight} energy efficient WDG-UAV-CSO produces 92.77% in sensor node. The proposed method E^{stop} energy efficient WDG-UAV-CSO produces 92.56% in sensor node. The proposed method E^{tot} energy efficient WDG-UAV-

CSO produces 91.30% in the energy consumption respectively.

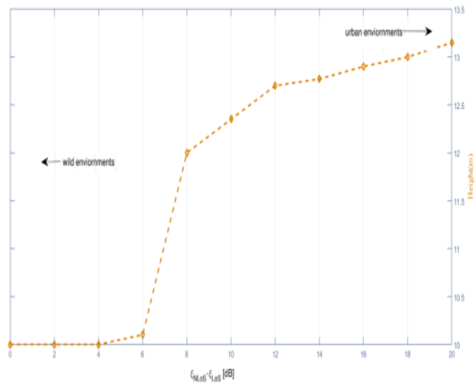

Figure 6: UAV altitude as a function

Figure 6 shows that the unmanned aerial vehicle is discussed in LoS and NLoS path loss altitude function. In this the proposed method energy efficient WDG-UAV-CSO detect the performance of diverse environment. Then the average height of the unmanned aerial vehicle is varying between the NLoS and LoS path loss. For wild environment, NLoS and LoS path loss are always equal, the unmanned aerial vehicle flies on low altitude as variance of path loss maximizes by higher altitude. Then the urban environment the greater shadow and obstacles maximizes NLoS path loss. Then the unmanned serial vehicle focused on the higher altitude to return to the best channels with LoS for diminishing the energy consumption.

5. CONCLUSION

In this manuscript, Energy Efficient Wireless Data Gathering with unmanned aerial vehicle using crow search optimization algorithm is examined. The proposed system optimizes the UAV stops the data collection with the minimum energy consumption subsequent to UAV for confirming the competent data collection. The proposed crow search optimization algorithm repeats to optimize the clustering based approach in unmanned aerial vehicle stops the position as well as sensors collected per stop for producing and resulting unmanned aerial vehicle. The simulation result shows that better result in communication and flight energies consumption compared to exiting method such as energy efficient WDG-UAV-TPO. The proposed method energy efficient WDG-UAV-CSO produces 96.66% better than existing energy efficient WDG-UAV-TPO respectively.

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