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Research Article

Efficient Data Collection in UAV-Assisted Cluster-Based Wireless Sensor Networks for 3D Environment: Optimization Study

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Unmanned aerial vehicles (UAVs) have been recently employed in combination with wireless sensor networks (WSNs) to collect data efficiently and improve surveillance effectiveness. This integration enhances the WSN infrastructure where UAVs are used as aerial base stations from which to access wireless sensors in hard-to-reach places within surveillance area. Consequently, the UAVs have become a promising solution to maintain reliability for the communication between wireless sensors and base station particularly in cases where infrastructure becomes unavailable such as hilly terrains and emergencies. However, UAVs encounter many challenges which mainly focus on their lifespan and efficient placement that improves the coverage and data collection. In this paper, a novel optimization study is presented to improve the lifespan of UAV-assisted cluster-based WSNs deployed in 3D environment. This optimization study is based on two algorithms: (1) *Particle Swarm Optimization* (PSO) which is employed to address the clustering problem in the WSN and (2) *Genetic Algorithm* (GA) which is employed to locate an efficient UAV placement to maximize the lifetime. The UAV-WSN system is evaluated by considering two metrics: *lifetime* and *throughput*. The simulation results show that varying UAV altitude has significant impact on both lifetime and throughput especially in the presence of different terrain. With increasing altitude, lifetime and throughput decrease as this loss can be as high as 94%. However, the proposed optimization plays a major role in combating these losses by redirecting the UAV to efficient placement corresponding to the new altitude level to maintain maximum lifetime and throughput. Moreover, the system lifetime concerning efficient UAV placement outperforms the one concerning centered placement at lower altitude, while the difference between two cases becomes less at higher altitude. Thereby, these outcomes may provide interesting measures for designing such integrated systems to achieve efficient data collection.

1. Introduction

Unmanned aerial vehicles (UAVs) are increasingly in demand due to their importance in providing robust and reliable communication systems for many civilian and military domains. Recently, the UAVs are integrated with other systems to create new sophisticated systems with more reliability and efficiency [1]. One of these systems, which is our focus in this study, is the integration of UAVs and wireless sensor networks (WSNs) to develop advanced system called UAV-WSN system. This system shows significant efficiency improvements in terms of operational lifetime, energy consumption, and data collection [2–4]. Such integration often results in higher degree of reliability and quality of service (QoS).

Generally, the UAV-WSN system is a collaborative hybrid system that provides a key solution to many issues associated with the design of typical WSNs. The limited power source in WSNs is a major design issue since the network consists of battery-powered sensors in which this problem has a significant impact on the network lifetime [5, 6]. Besides, the WSNs encounter other limitations in terms of coverage and data collection especially in hard-to-reach areas such as rugged hilly terrain, and this affects the effectiveness of surveillance systems as well as emergency situations where timely data collection is very important in saving lives.

In order to address the aforementioned problems and limitations, the paper proposes composite solutions: (1) employ cluster-based WSNs and (2) employ UAV to act as an aerial base station to access sensor nodes. Moreover, this integrated system between WSNs and UAV is deployed in 3D environment to model hard-to-reach places and to imitate cases of emergencies where the UAVs can provide a solution through the integration with WSNs. Consequently, the UAVs improve the accessibility and scalability issues of WSNs and support large-scale surveillance systems.

On the other hand, the paper points out critical issues regarding UAVs: lifetime and efficient placement. These issues have significant impact on the efficiencies of data collection and field coverage. Therefore, figuring out an appropriate solution to address these challenges is always the major target for the current research works [7].

The need for this type of integrated systems has increased and spread on a global scale. These systems play a vital role in the formation of emergency infrastructure in the case of severe damage to urban infrastructure due to natural disasters such as wildfires, floods, or earthquakes. Thereby, establishing an emergency wireless communication network supported by UAVs is one of the requirements for maintaining connectivity and coverage for geographical apart areas especially for the aforementioned cases [8–10].

Moreover, the paper sheds light on cases where the clustering approach is useful to keep the communication with the distributed users along different clusters supported by the UAV to achieve the best coverage for the longest possible period of time. The clustering technique is considered one of the promising solutions for efficient data collection. The surveillance region, which consists of randomly deployed sensor nodes, is divided into subregions called clusters where each one consists of a subset of sensor nodes called *cluster members* (CMs). The cluster is responsible for collecting the sensory data from its members and sending it to the designated sensor node called *cluster head* (CH). Then, the CHs transmit the collected data to the UAV through the uplink. This entire system which is depicted in Figure 1 is called UAV-assisted cluster-based WSN, which basically improves the energy efficiency of the WSNs, which is results in improving the efficiency of data collection as well.

This paper proposes a novel optimization study to maximize the lifetime of UAV-WSN systems based on clustering. Besides, the proposed study introduces the 3D environment in the network design to support the hilly terrain as well as hard-to-reach regions. Furthermore, this work investigates the efficient placement of the UAVs in order to increase the efficiency of data collection.

The novelty of our work is to find the best solution for clustering problem using PSO optimization taking into account the hilly terrain of the surveillance region. The best solution means to find the optimal centroids of clusters in a 3D environment which is the NP-hard problem. Besides, the method produces an even distribution of centroids throughout the surveillance region. The CH selection does not directly determined by the PSO algorithm. However, in this research, the CH selection process was incorporated in a protocol that will be discussed later, in which several parameters are considered including the distance from centroid, residual energy, and minimum path loss considering the 3D environment for upload transmission to UAV.

Additionally, some clustering methods that follow the LEACH protocol [11] do not ensure the optimum outcomes from clustering. Subsequently, some literature enhanced the clustering problem by using optimization techniques such as [12], which presented energy-efficient cluster head selection algorithm based on the PSO. In this work, the authors first presented a Linear Programming (LP) formulation for CH selection problem. Then, they proposed the PSO-based CH selection algorithm. This work considered number of factors including the intracluster distance, sink distance, and residual energy of sensor nodes. Also, in [13], the authors proposed an energy-aware clustering method for WSNs using PSO algorithm by simultaneously minimizing the intracluster distance and optimizing the energy consumption. However, most of the optimization-based clustering methods do not consider the path loss model or the nature of the surveillance region.

Generally, the PSO has a significant impact in CH selection, but it does not directly select the CH. The optimization side plays an important role in both intracluster communication through data transmission from CMs to CH [14] and intercluster communication through uplink transmission from CHs to UAV which act as an aerial BS.

The main objective of this paper is to address the impact of the UAV-WSN collaborative system to improve the lifespan of cluster-based WSNs along with data collection. In contrast to most of the previous literature, which focuses on maximizing the lifespan of the cluster-based WSNs, this study investigates the extending of the WSN's lifespan through the use of UAVs and how this technology can affect energy efficiency as well as data collection efficiency. The expected outcomes of this research work is to get improvement for the typical design of the WSNs in terms of operational lifetime and data collection. Also, this research demonstrates in practice the important needs for the integrated systems in emergency situations as well as 3D environment or mountainous terrain in order to collect timely data.

Motivation and Contribution: the motivation of this research is summarized as follows. Wireless sensors are randomly deployed across certain areas where they will form a WSN. Sensory data is collected from these power-limited sensors. Sometimes, these sensors are deployed in inaccessibility or hard-to-reach places, which leads to a lack of data. Furthermore, there are some situations, such as emergencies, military regions, or borders, where an assisted or collaborative system is required to work jointly with WSNs for efficient data collection. Therefore, the UAV is integrated with the WSN to form the UAV-WSN system and achieve the main objective, which is to maintain the availability and reliability of data collection as long as possible. Thus, this work

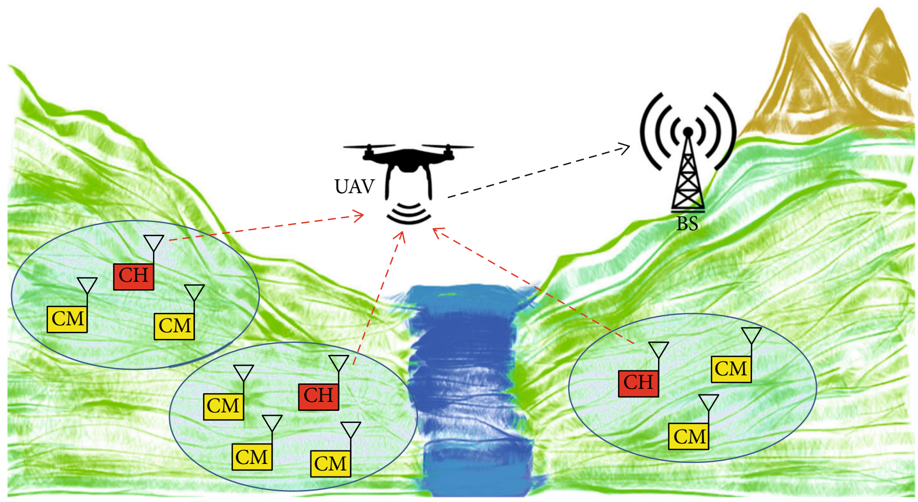


FIGURE 1: General model for UAV-assisted cluster-based WSN deployed in a rugged hilly terrain to collect data efficiently.

presents an improvement in the data collection efficiency by maximizing the lifetime of the UAV-WSN system, which supports the 3D environment. The proposed idea is innovative and different from the previous one in terms of the optimization problem and the system model.

The main contributions of this work are briefly listed in the following points:

(i) UAV-assisted cluster-based WSNs are modeled in a 3D environment that mimics the nature of different terrain such as hilly terrain and hard-to-reach regions

(ii) Energy consumption model of the proposed network was derived taking into account both the transmit signal energy and the circuit energy

(iii) Optimization problem to maximize the lifetime for the proposed UAV-WSN system is formulated

(iv) Particle Swarm Optimization (PSO) is used in the clustering algorithm for the WSN, which is unique work to the best of our knowledge

(v) Genetic Algorithm (GA) is employed to locate an efficient 3D UAV placement that maximizes the lifetime of the UAV-WSN system

(vi) The lifetime for the proposed system is investigated at different altitudes of the UAV

(vii) The throughput for the uplink transmission from cluster heads to UAV is investigated according to different altitudes of UAV

(viii) The performance analysis for the proposed system is studied taking into account two scenarios of the UAV placement: centered placement at the surveillance region and efficient placement (i.e., optimization-based placement)

The rest of the paper is organized as follows. Section 2 presents literature reviews. Section 3 demonstrates molding and problem formulation. Section 4 discusses the performance evaluations of the proposed work. Finally, Section 5 concludes the paper.

2. Literature Review

Many research studies have been proposed to explain what motivates utilizing UAVs in WSN. Although the literature covers a wide variety of such research studies, this review will focus on utilizing UAVs in extending the uplink transmission times for wireless devices.

2.1. Single-UAV Scenario. In [15], the problem of a single-UAV placement is studied, where the objective function of the optimization problem is to find an efficient placement of a single UAV that prolongs the lifetime of indoor wireless devices. The constraint sets of the optimization problem are shown to be represented as a convex set in terms of three variables, and an algorithm for finding an efficient placement for the UAV is proposed. In [16], the authors study an uplink power control problem for UAV-assisted wireless communications. They jointly optimize the UAV's placement, wireless devices' assigned bandwidth, antenna beamwidth, and transmit power to minimize the total power for uplink while meeting the minimum rate need. To obtain a suboptimal solution, a low-complexity iterative algorithm is proposed. According to numerical results, the suggested approach performs well in terms of uplink sum power savings.

In [17], the authors study a cognitive UAV-enabled IoT network, in which cognitive Internet of Things (IoT) devices upload data to the UAV hub via a NOMA protocol in the primary network's spectrum. The objective function is to maximize the minimum lifetime of IoT devices by jointly optimizing the transmit power, UAV placement, and decoding order subject to interference-power constraints in the presence of the imperfect channel state information. They use Lagrange duality to solve the formulated nonconvex mixed-integer programming problem by jointly optimizing the UAV placement and transmit power for a given decoding order and obtaining the globally optimal solution. Then, they use an exhaustive search to find the best decoding order, which is suited to small-scale settings. They present a low-complexity suboptimal approach for large-scale situations by converting the original problem into a more tractable equivalent form and using the successive convex approximation technique and penalty function method to solve it. The suggested design outperforms the benchmark schemes significantly, according to numerical results.

In [18], the authors investigate energy-aware data collection in robot network clusters. A cluster head robot in each cluster assigns one collaborative task to each cluster member robot and gathers data from cluster members, while a UAV visits a subset of cluster head robots to gather data from them due to battery limitations. The UAV's decision to visit the subset of cluster heads is limited by a number of variables, such as the amount of remaining battery power and the positions and data quality of each cluster head robot. Cluster head robots are used as data relay nodes by nonvisited cluster head robots. The UAV is utilized to minimize the total joint costs of data qualities and energy consumption of cluster head robots. A similar scenario is studied in [19] with a different objective function, in which the optimization problem is aimed at minimizing the UAV total energy consumption coupled to minimum cost data collection from cluster head robots by visiting optimally a portion of the cluster head robots. In [20], the authors present an efficient framework to realize efficient data collection from WSNs, where a backup UAV carrying batteries travels alongside the primary UAV to make up for the UAV's lack of energy while the primary UAV is sent out to gather the aggregated data from cluster heads. The optimization problem is aimed at finding the minimum mission time for a complete round of data collection, which is formulated as a coordinated traveling salesman problem with battery constraints and is solved by utilizing a heuristic algorithm. The authors of [21] study the UAV placement problem for critical nodes in emergency networks. Two different optimization problems are formulated based on the nature of node criticality, namely, capacity maximization and age of information minimization. The first optimization problem is aimed at enhancing the QoS for critical nodes, whereas the second optimization problem is focused on nodes carrying critical information.

2.2. Multiple-UAV Scenario. The authors of [7, 22] investigate the UAV placement problem to determine the positions of a group of UAVs that optimize uplink transmission duration of ground wireless devices until the first wireless device runs out of battery. For the general case of many UAVs, they propose an efficient technique to optimize the lifetime of wireless devices. They also study the problem of minimizing the number of UAVs needed to service ground wireless devices so that each wireless device's uplink transmission time is more than or equal to a predetermined threshold. They present two effective methods for reducing the number of UAVs required to serve wireless devices. In [23, 24], the authors investigate the problem of efficient 3D placements for a set of UAVs in a mmWave network. The objective function of the optimization problem is aimed at finding the most effective UAV deployments that maximize the total uplink transmissions' time duration of ground wireless devices in a mmWave network. Due to its intractability, they propose a heuristic algorithm to solve the optimization problem.

The authors of [25] optimize the 3D UAV placement and path loss compensation factor to improve user coverage in uplink transmission. Compared to the baseline scheme, simulation results show that optimizing the UAV height and path loss compensation factor resulted in greater coverage and throughput. Simulations were performed for four alternative uplink power control scenarios, with the maximum power transmission scenario serving as a benchmark for comparison. The simulation results show that when both aerial and macrouser devices transmit with power control, coverage is increased. In [26], the authors are interested in maximizing the lifetime of ground wireless devices for communications. The ground user's lifetime is defined as the amount of time that a ground wireless device can communicate before the battery runs out. They use a frequency division multiplexing uplink system in which multiple UAVs serve the ground users. They propose an efficient approximation approach using judicious problem reformulation and successive convex approximation techniques to solve a joint user association, power control, bandwidth allocation, and UAV deployment problem for lifetime maximization. They show that in the case of a single UAV, the problem can be solved globally via simple bisection. The simulation results show that the proposed algorithms can reach near-optimal performance and outperform heuristic approaches significantly.

The authors in [27] study the problem of a UAV-assisted network lifetime maximization in the presence of several sources of interference, where the UAVs are used to collect data from a set of wireless sensors. They show that because the required transmission powers of the UAVs are directly related to their locations in space, the placement of the UAVs plays a major role in extending the network's lifetime. The UAVs transmit the obtained data to a primary UAV called the leader, which is in charge of forwarding the data to the base station via a backhaul UAV network in the suggested scenario. Due to the problem's nonconvexity, they use spectral graph theory tools to solve it. The results of simulations show that the proposed strategy can greatly increase the UAV network's lifetime.

The authors in [28] investigate the efficient deployment and mobility of multiple UAVs that are utilized as aerial base stations to collect data from ground IoT devices. A novel framework is proposed for optimizing UAVs' 3D positioning and mobility, device-UAV association, and uplink power control to enable reliable uplink communications for IoT devices with a minimum total transmit power. First, the efficient UAV positions and associations are identified based on the locations of active IoT devices at each time instant. The UAVs' optimal mobility patterns are then studied to dynamically serve the IoT devices in a time-varying network. The time instances at which the UAVs must update their locations are calculated based on the IoT devices' activation process. Furthermore, the optimal 3D trajectory of each UAV is determined so that the total energy used for UAV mobility while serving IoT devices is minimized. According to simulation results, the proposed approach reduces the total transmit power of IoT devices by 45% compared to deploying stationary aerial base stations.

In [29], the optimal set of load-balanced cluster heads is found using the Salp-Swam optimization method, and each UAV's optimal path is estimated using a metaheuristic based on differential evolution. In order to shorten the time required for data collection, multiple UAVs are deployed. All UAVs leave from a base station to collect data, travel to the cluster heads, and then, return to the base station. The proposed scheme's performance outperforms two well-known existing schemes in terms of travel time. The authors of [30] present a load-balanced cluster formation scheme and a noncooperative cluster head selection algorithm based on game theory. A hybrid metaheuristic-based optimal path planning algorithm is proposed by combining the best aspects of Dolphin Echolocation and Crow Search metaheuristic techniques to provide timely delivery of sensing information using UAVs. For both the load-balanced cluster head selection problem and the best path planning problem, a novel objective function is formulated. Result analyses show that the proposed scheme significantly outperforms the most recent schemes.

2.3. Metaheuristic Techniques. The works in [31–35] proposed different methods based on metaheuristic techniques for cluster head selection in IoT-WSN. In [31], an energy-efficient cluster head selection using two metaheuristic algorithms, namely, Competitive Swarm Optimization and Harmony Search Algorithm was proposed. The developed approach provided a global search with a fast convergence rate for energy-efficient cluster-based WSNs, using different energy-saving strategies such as clustering methods and optimal route selection for WSN devices. Moreover, the authors in [32], developed a hybrid metaheuristic approach, namely, Whale Optimization Algorithm with Simulated Annealing algorithm, to minimize the device's energy consumption in IoT-based WSNs and to divide the IoT network into clusters and select the best cluster head for each group. The authors in [33] proposed a selection process based on computational intelligence techniques, namely, neuro-fuzzy inference system-based routing for intercluster transmission in IoT-WSN. Specifically, this work developed a swarm intelligence model with an adaptive neuro-fuzzy inference system-based routing for clustered WSNs, to select the cluster heads and efficient routes for multihop communication in the WSN. The study in [34] developed a metaheuristic approach using an adaptive neuro-fuzzy inference system for decision-making called the MANFIS-DM approach for UAV systems. The proposed approach sets the UAV networks into clusters and classified the images into appropriate class labels. Moreover, this approach designed a fitness function for cluster head selection.

The authors of [12] propose an energy-efficient cluster head selection algorithm based on PSO. They take into account a number of factors, including the intracluster distance, sink distance, and residual energy of sensor nodes, to determine how energy-efficient the proposed PSO approach is. Additionally, they demonstrate cluster formation in which sensor nodes without cluster heads associate with their cluster heads according to the weight function. The algorithm is thoroughly tested using various WSN scenarios, number of sensor nodes, and number of cluster heads. To show the proposed algorithm's superiority, the results are compared with other existing algorithms.

The problem of energy-balanced node clustering and routing between cluster heads and the sink are taken into consideration in [36]. An enhanced cuckoo search-based energy balanced node clustering protocol is utilized for the problem of energy-balanced node clustering. For the data packet routing between cluster heads and the sink, they propose an improved harmony search-based routing protocol. The average energy consumption, the number of active nodes, the number of nodes that have died, and the network lifetime are used to assess the performance of the proposed integrated clustering and routing protocol. The integrated clustering and routing protocol that is being proposed based on Cuckoo-Harmony Search outperforms state-of-the-art protocols.

3. Modeling and Problem Formulation

This section presents the main structure of the proposed work. It demonstrates the UAV-WSN system model and then formulates the optimization problem in terms of clustering and optimal UAV placement by employing both algorithms PSO and GA, respectively.

3.1. UAV-WSN System Model. The UAV-assisted cluster-based WSN model under consideration (Figure 2) consists of n sensor nodes $S = \{s_1, s_2, s_3, \cdots, s_n\}$ grouped into k clusters, such that $L = \{C_1, C_2, C_3, \cdots, C_k\}$. Each kth cluster is a subset of L in which it consists of j cluster members such that $C_k = \{m_1, m_2, m_3, \cdots, m_j\}$, where $|C_v|$ not necessarily equal to $|C_w|, \forall C_v, C_w \in L$. Besides, each cluster is dominated by predetermined *Cluster Head* (*CH*). In this work, the *CH* is elected according to its *maximum* residual energy (E_{res}) in which the residual energy should satisfy a threshold value (i.e., $E_{\text{res}} \geq E_{\text{th}}$), and this process is performed by employing PSO which will be explained later in Section 3.2.1. Accordingly, the proposed model comprised i cluster heads, such that $H = \{h_1, h_2, h_3, \cdots, h_i\}$.

Consequently, the kth cluster is responsible for collecting data and transmitting them to its corresponding ith CH by means of intracommunication [14]. On the other hand, the ith CH is responsible for transmitting the collected data to the UAV by means of uplink transmission. This study assumes that the channel model for CM-CH is Rayleigh flat fading with path loss, and for CH-UAV is free-space path loss. Mainly, the proposed system model is constructed based on two submodels: (1) CM-CH communication model and (2) CH-UAV communication model. These two submodels are explained in more detail in the following

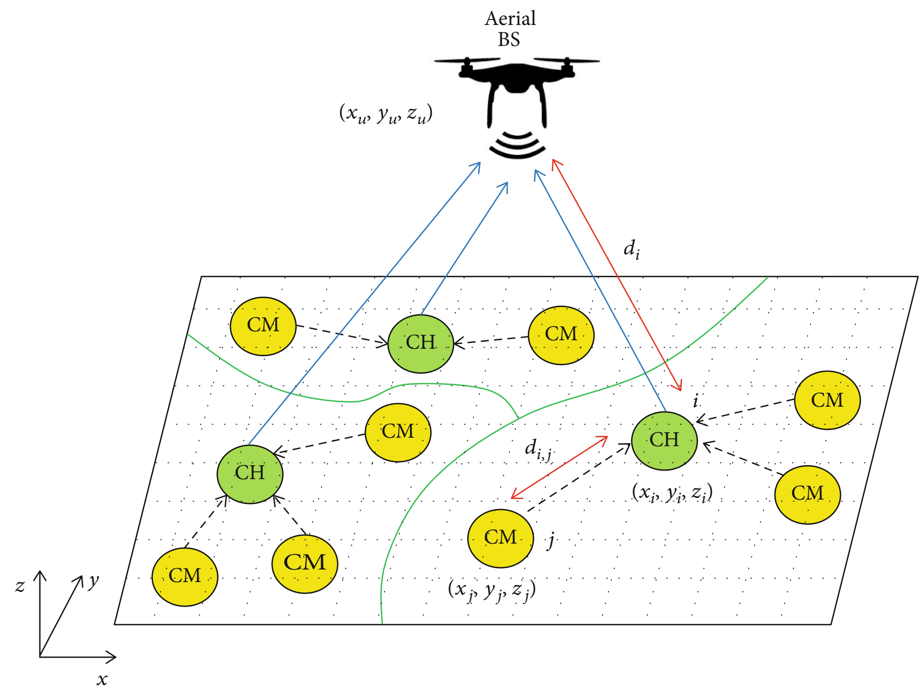


Figure 2: Proposed model for UAV-assisted cluster-based WSN showing uplink transmission form CHs to UAV for the collected data from CMs.

subsections. All parameters used in formulating the system model are listed in Table 1.

The challenges for the successful deployment of a UAV in cluster-based wireless sensor networks include spectrum efficiency, energy consumption, deployment time, backhaul, and cost of deployment [37]. In this research work, we use a rotary-wing UAV.

3.1.1. Cluster Members-Cluster Head Communication Model. This section presents the *ground communication model* adopted in this study. The communication model for CM-CH addresses the wireless communication and energy consumption required for data transmission between CMs and CH as depicted in Figure 2. The communication model described in [38–41] is adopted to model the communication between CMs and CH.

For the 3D cluster-based network, the CM-CH link at distance

$$d_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2}; \forall i \in H, \forall j \in C_k, \tag{1}$$

with vth power path loss has power gain factor given by [39]

$$G_d = \frac{P_{tx}^m}{P_{rx}^h} = G_1 d_{i,j}^v M_l, \tag{2}$$

where G_1 which is the factor for antenna gain at distance 1 meter is calculated by [39, 41]

$$G_1 = \frac{(4\pi)^2}{\mathcal{G}_{tx}\mathcal{G}_{rx}\lambda^2}, \tag{3}$$

where $(\mathcal{G}_{tx})$ and $(\mathcal{G}_{rx})$ are the antenna gains for both transmitter and receiver, and λ is the wavelength.

As CM (*transmitter*) transmits a signal $x(t)$ with power P_{tx}^m, it will be added to noise signal $n(t)$ (Figure 3), which is additive white Gaussian noise (AWGN) in this study. Thereafter, the signal-to-noise ratio (*SNR*) for the received signal $y(t) = x(t) + n(t)$ at the CH (*receiver*) is given by [39]

$$\gamma = \frac{P_{rx}^h}{2B\sigma^2 N_f}, \tag{4}$$

where B is the channel bandwidth, σ^2 is the power spectral density of the AWGN, and N_f is the receiver noise figure. Consequently, the total noise power is $N = 2B\sigma^2 N_f$.

From Equation (2) and Equation (4), taking into account that $P_{tx}^m = P_{rx}^h G_d$, the *SNR* becomes

$$\gamma = \frac{1}{G_d} \cdot \frac{P_{tx}^m}{2B\sigma^2 N_f} \Rightarrow \gamma = \frac{1}{G_1 d_{i,j}^v M_l} \cdot \frac{P_{tx}^m}{2B\sigma^2 N_f}. \tag{5}$$

In this work, the *SNR* is considered as an important constraint since it indicates the channel quality between CMs and CH within each cluster.

Table 1: Parameters used in formulating the problem.

Parameter	Description
$d_{i,j}$	CM-CH distance in meters, $\forall i \in H, \forall j \in C_k$.
d_i	CH-UAV distance in meters, $\forall i \in H$.
$E^m_{i,j}$	Total energy consumption at CM, $\forall i \in H, \forall j \in C_k$.
$P^m_{tx,i,j}$	Transmitted power from jth CM to ith CH.
$E^m_{tx,i,j}$	Transmitted energy from jth CM to ith CH.
$P^h_{rx,i}$	Received power at ith CH.
$P^h_{tx,i}$	Transmitted power from ith CH to UAV.
$E^h_{tx,i}$	Transmitted energy from ith CH to UAV.
B	Channel bandwidth.
σ^2	Power spectral density of the AWGN.
N_f	Receiver noise figure.
ν	CM-CH link path loss exponent.
L_i	CH-UAV path loss, $\forall i \in H$.
$\tau_{i,j}$	Transmission time from jth CM to ith CH.
τ_i	Uplink transmission time from ith CH to UAV.
E	Total energy consumption for transmitting K-bit packet.
K	Message length in bits.
E_c	Energy consumption for circuit.
P_c	Power consumption for circuit.
$P_{c,tx}$	Power consumption for transmitter circuit.
$P_{c,rx}$	Power consumption for receiver circuit.

(1) Energy Consumption Model. The energy consumption model addresses both transmitted energy (E_t) and circuit energy (E_c). Thereby, each jth CM within kth cluster consumes E (Joule) to transmit *K-bit* packet to its corresponding ith CH during τ period of time which is given by

$$E^m_{i,j} = E^m_{tx,i,j} + E^m_{c,j}, \forall i \in H, \forall j \in C_k. \tag{6}$$

Each jth CM consumes energy for transmitted signal to i th CH which is calculated by

$$E^m_{tx,i,j} = P^m_{tx,i,j} \cdot \tau_{i,j}, \forall i \in H, \forall j \in C_k. \tag{7}$$

In order to investigate different data rates (i.e., modulation order), the M-ary Quadrature Amplitude Modulation (MQAM) is adopted in the communication system between the ith *CH* and jth *CM* because it is commonly used for data transmission in the cutting edge systems.

In the MQAM system, the number of bits per symbol is $b = \log_2 M$ bits (i.e., M is the modulation order, where $M = 2^b$). The *K-bit* packet has K/b symbols to be transmitted, and the symbol duration time for each symbol is τ_s, then

$$\frac{K}{b} = \frac{\tau_{i,j}}{\tau_s} \Rightarrow b = \frac{K\tau_s}{\tau_{i,j}}. \tag{8}$$

The channel bandwidth in MQAM, which is assumed to be fixed, is $B = 1/\tau_s$ when the squared pulses are employed [39]; then, the number of bits is

$$b = \frac{K}{B\tau_{i,j}}. \tag{9}$$

Therefore, the duration time to transmit K *-bit* packet is

$$\tau_{i,j} = \frac{K}{Bb} \Rightarrow \tau_{i,j} = \frac{K}{B \log_2 M}. \tag{10}$$

Furthermore, the E_{tx} for each *CM* is calculated at predefined bit error rate (*BER*) P_b corresponding to *SNR* (γ). For the case of MQAM, the *BER* is upper bounded by [42]

$$P_b \le \frac{4}{\log_2 M}\left(1 - \frac{1}{\sqrt{M}}\right) e^{-(3\gamma/2(M-1))}. \tag{11}$$

From Equation (11), we can solve it for γ to get an upper bound as follows:

$$\gamma \le \frac{2}{3}(M-1) \ln \left(\frac{4\left(1-\left(1/\sqrt{M}\right)\right)}{P_b \log_2 M}\right). \tag{12}$$

Equation (12) points out to the upper bound of the *SNR* since the objective is get maximum transmit energy. By substituting the value of γ from Equation (5) in Equation (12), then solving it for $P^m_{tx,i,j}$, we get

$$P^m_{tx,i,j} = \frac{4}{3} G_d B \sigma^2 N_f (M-1) \ln \left(\frac{4\left(1-\left(1/\sqrt{M}\right)\right)}{P_b \log_2 M}\right). \tag{13}$$

Finally, $E^m_{tx,i,j}$ can be calculated by substituting Equation (13) into Equation (7), and it becomes

$$E^m_{tx,i,j} = \frac{4}{3} G_d B \sigma^2 N_f (M-1) \ln \left(\frac{4\left(1-\left(1/\sqrt{M}\right)\right)}{P_b \log_2 M}\right) \cdot \tau_{i,j}. \tag{14}$$

From Equation (14), it can be noticed that the transmit energy $E^m_{tx,i,j}$ for the jth CM decreases monotonically as long as the transmission time $\tau_{i,j}$ decreases provided that both the packet size K and channel bandwidth B are constant values [39].

Regarding *circuit energy consumption* E_c, in contrast to transmit energy E_{tx}, it does not depend on the transmission distance d. As depicted in Figure 3, depending on the role of

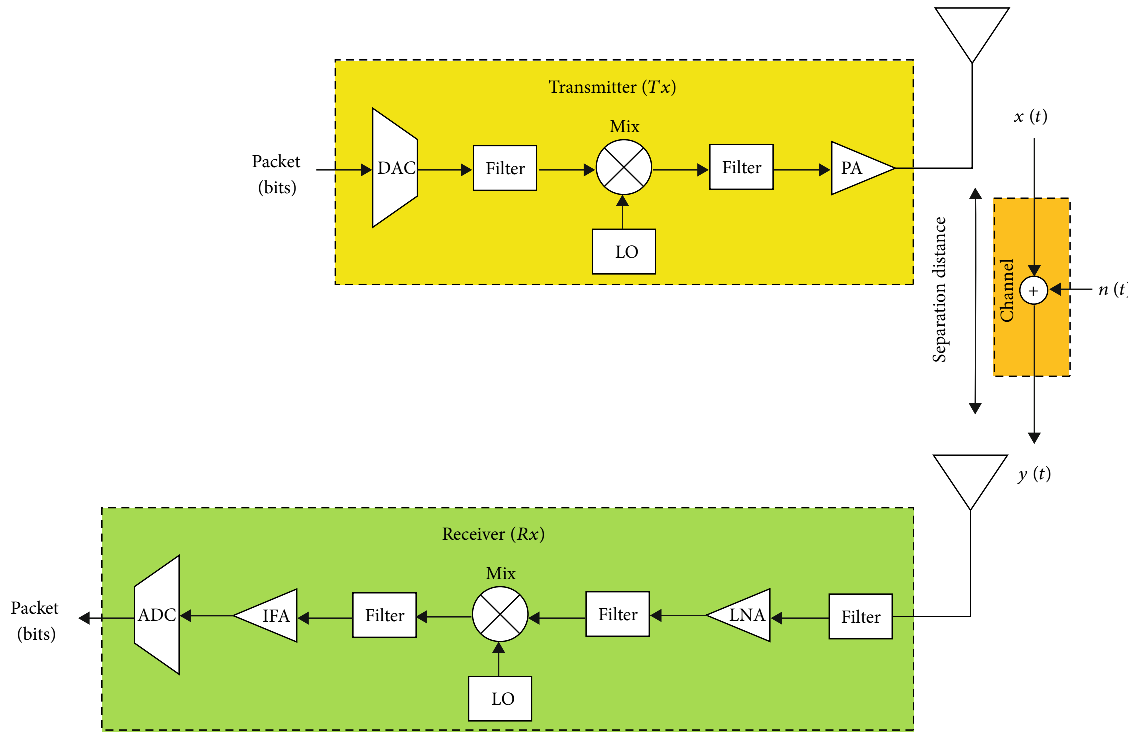


FIGURE 3: Transmitter-receiver communication model [39].

the sensor node (i.e., transmitter or receiver), the model is generally given by

$$E_c = P_c \cdot \tau, \tag{15}$$

where P_c is the total circuit power consumption and τ is the duration time for transmission. P_c is calculated by

$$P_c = P_{c,tx} + P_{c,rx}, \tag{16}$$

where $P_{c,tx}$ is the transmitter circuit power consumption given by

$$P_{c,tx} = P_{\text{DAC}} + P_{\text{Syn}} + P_{\text{Mix}} + P_{\text{Filt},tx}. \tag{17}$$

Also, $P_{c,rx}$ is the receiver circuit power consumption given by

$$P_{c,rx} = P_{\text{ADC}} + P_{\text{Syn}} + P_{\text{Mix}} + P_{\text{Filt},rx} + P_{\text{IFA}} + P_{\text{LNA}}. \tag{18}$$

The circuit blocks which are depicted in Figure 3 and employed in Equation (17) and Equation (18) are digital-to-analog converter (DAC), analog-to-digital converter (ADC), frequency synthesizer, mixer with local oscillator (LO), transmitter filter, receiver filter, intermediate frequency amplifier (IFA), and low-noise amplifier (LNA).

Moreover, the transmitter also has power amplifier (*PA*) component which has a significant impact on the total power consumption as it has a relation with transmit signal power. The power consumption of the PA is given by [39].

$$P_{\text{Amp}} = \alpha \cdot P_{tx}, \tag{19}$$

where α is the power amplifier coefficient, and in case of MQAM system, $\alpha = (\xi/\eta) - 1$ with ξ is peak to average ratio (PAR), $\xi = 3((\sqrt{M} - 1)/(\sqrt{M} + 1))$, which is dependent on modulation scheme and its order, and η is drain efficiency for RF power amplifier.

As a result, the total energy consumption to transmit K *-bit* packet from source (jth CM) to destination (ith CH) over distance $d_{i,j}$ during $\tau_{i,j}$ transmission time can be obtained by substituting Equation (14) and Equation (15) into Equation (6) as follows:

$$\begin{aligned} E_{i,j}^{m} &= \left(P_{tx,j}^{m} + P_{c,j}^{m} + P_{\text{Amp}}\right) \cdot \tau_{i,j} \\ &= \left(P_{tx,i,j}^{m} + P_{c,j}^{m} + \alpha P_{tx,i,j}^{m}\right) \cdot \tau_{i,j} \\ &= (1 + \alpha) P_{tx,j}^{m} \cdot \tau_{i,j} + P_{c,j}^{m} \cdot \tau_{i,j}. \end{aligned} \tag{20}$$

Hence, we get

$$\begin{aligned} E_{i,j}^{m} = {} & \left((1 + \alpha) \frac{4}{3} G_d B \sigma^2 N_f (M - 1) \ln \left(\frac{4\left(1 - \left(1/\sqrt{M}\right)\right)}{P_b \log_2 M} \right) \right) \\ & \cdot \tau_{i,j} + P_{c,j}^{m} \cdot \tau_{i,j}. \end{aligned} \tag{21}$$

Therefore, the energy consumption per information bit is given by $E_{bit}^{m} = E^{m}/K$. Moreover, in Equation (21), it can be noticed that the circuit energy consumption has a significant impact on the total energy consumption. That is, for minimum transmission time, the transmission energy consumption is maximized; in contrast, the circuit energy consumption is minimized [39]. Thus, there is an optimal value for the transmission time in order to minimize the total energy consumption. Particularly, for simplicity purposes, the modulation order is not considered. Instead, a fixed data rate is employed in the proposed system. In future work, this issue will be taken into account.

(2) Maximum Power Constraint. Since wireless sensors are limited in power due to battery limitations, the total power consumption is restricted by the availability of battery power. Let $P_{\max}$ be the maximum power available to transmit K *-bit* packet in which it is equal to the maximum battery output at the transmitter, ignoring all power consumption from other circuit components [39]; then, the maximum power constraint is

$$(1+\alpha)P_{tx} + P_{c,tx} \le P_{\max}. \tag{22}$$

Therefore, the maximum transmit power consumption is upper bounded by [40]

$$P_{tx,\max} \le \frac{P_{\max} - P_{c,tx}}{(1+\alpha)}. \tag{23}$$

Consequently, for the case of MQAM system power constraint becomes

$$(1+\alpha)\frac{4}{3}G_d B\sigma^2 N_f (M-1)\ln\left(\frac{4\left(1-\left(1/\sqrt{M}\right)\right)}{P_b \log_2 M}\right) + P_{c,tx} \le P_{\max}. \tag{24}$$

3.1.2. Cluster Head-UAV Communication Model. This section presents the *ground-to-UAV communication model* employed in this study. The communication model mentioned in [7] is adopted in this work to model the communication between CHs and UAV. It is assumed that the channel between CHs and UAV is line of sight (*LoS*) as the free space path loss model is employed. The path loss between the ith CH and the UAV is given by

$$L_i = \left(\frac{4\pi d_i f}{c}\right)^2, \forall i \in H, \tag{25}$$

where d_i is the uplink distance between the ith CH and the UAV, and it is given by

$$d_i = \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + (z_i - z_u)^2}. \tag{26}$$

Consider an uplink transmission from the ith CH located at (x_i, y_i, z_i) and UAV located at (x_u, y_u, z_u). Then, the data rate given by

$$C_i = B_i \log_2\left(1 + \frac{P_{tx,i}^{h}/L_i}{N}\right), \forall i \in H, \tag{27}$$

where $P_{tx,i}^{h}$ is the transmit power from the ith CH to UAV, N is the noise power, and B_i is the channel bandwidth for the i th CH. If it is assumed that B_u is the bandwidth for the UAV, then $B_i = B_u/|H|$, where $|H|$ is the cardinality of set H (i.e., number of all CHs in H). Besides, if it is assumed that all sensor nodes have same data rate R, then the minimum transmit power to meet this requirement is given by

$$P_{tx,i}^{h} = \left(2^{R\cdot|H|/B_u} - 1\right)NL_i, \forall i \in H. \tag{28}$$

Consequently, the corresponding minimum transmit energy is given by

$$E_{tx,i}^{h} = P_{tx,i}^{h}\tau_i, \forall i \in H. \tag{29}$$

Each CH is served by a UAV for a time τ_i seconds in which it depends on the residual energy $E_{\text{res},i}$ of the battery.

3.2. Problem Formulation. In this research, the optimization study under consideration employs two algorithms as will be explained in the next sections: (1) *Particle Swarm Optimization* (PSO) and (2) *Genetic Algorithm* (GA). In PSO, the fitness function is an objective function representing the optimized problem. The goal of the PSO algorithm is to find an efficient solution to the optimization problem by finding the set of parameters that minimize or maximize the fitness function. Specifically, the main objective of this work is to find the efficient placement of the UAV subject to maximizing the lifetime of the cluster-based wireless network operated jointly with the UAV. In this paper, lifetime T is the fitness function which is defined as the sum of the time duration for CM-CH transmission and CH-UAV uplink transmission.

The formulation of the proposed *optimization model* is given by

$$\max_{(X_u,Y_u,Z_u)} T = \underbrace{\sum_{i=1}^{|H|}\sum_{j=1}^{|C_k|}\tau_{i,j}}_{\text{CM-CHTransmission}} + \underbrace{\sum_{i=1}^{|H|}\tau_i}_{\text{CH-UAVUplink}}, \tag{30}$$

subject to

$$P_{tx,i}^{h} \le P_{\max}, \forall i \in H, \tag{31a}$$

$$E_{tx,i}^{h} \le E_{\text{res},i}, \forall i \in H, \tag{31b}$$

$$E_{\text{res},i} \ge E_{\text{th}}, \forall i \in H, \tag{31c}$$

$$\tau_{i,j} + \tau_i \ge \tau_{\text{th}}, \forall i \in H, \forall j \in C_k, \tag{31d}$$

$$\gamma_j \ge \gamma_{\min}, \forall j \in C_k, \tag{31e}$$

$$P^{m}_{tx,i,j} \leq P_{\max}, \forall i \in H, \forall j \in C_k, \quad (31f)$$

$$x_{\min} \leq X_u \leq x_{\max}, \quad (31g)$$

$$y_{\min} \leq Y_u \leq y_{\max}, \quad (31h)$$

$$z_{\min} \leq Z_u \leq z_{\max}. \quad (31i)$$

The objective function Equation (30) is to maximize the lifetime of the cluster-based network in which it consists of individual transmission time for all CMs, within the kth cluster, jointly with their corresponding CHs.

The optimization problem formulation subject to set of constraints from Equation (31a) to Equation (31i) explained as follows:

(i) Constraint Equation (31a) ensures that the maximum transmit power for each CH should not exceed its maximum transmit power. It can be calculated from Equation (28)

(ii) Constraint Equation (31b) ensures that the total energy consumed by CH should not exceed its battery energy level $E_{\mathrm{res},i}$. It can be calculated from Equation (29)

(iii) Constraint Equation (31c) ensures that the available battery energy level $E_{\mathrm{res},i}$ should be greater than E_{th}.

(iv) Constraint Equation (31d) ensures that both CMs and their corresponding CHs is served for a time greater than τ_{th}

(v) Constraint Equation (31e) is the *SNR* (γ) constraint corresponding to certain *BER*, and it can be calculated from Equation (12)

(vi) Constraint Equation (31f) is the maximum power constraint which ensures that the maximum transmit power for each CM should not exceed its maximum transmit power, and it can be calculated from Equation (23)

(vii) Constraint Equation (31g) to Equation (31i) represent the minimum and maximum allowed values for the coordinates of the UAV

Clustering sensor nodes is an efficient topology control strategy for reducing sensor node energy consumption and maximizing WSN lifetime. In a cluster-based WSN, the cluster heads face some additional burdens for operations like as data collecting, data aggregation, and data transfer to the base station. As a result, balancing the load on the cluster heads is a difficult task for the WSNs' long-term operation. For a WSN, load-balanced clustering is well-known to be an NP-hard problem [43]. In this paper, the PSO is employed for the clustering design problem, and the GA is employed to locate an efficient 3D UAV placement that maximizes the lifetime of the UAV-WSN system.

3.2.1. Clustering Approach Using Particle Swarm Optimization (PSO). This section presents the mathematical formulation of the clustering problem using *PSO* which is considered as an optimization problem. PSO is a metaheuristic algorithm that can be employed for clustering problems. In this section, we provide a comprehensive discussion of PSO clustering algorithms with their pseudocode, and we provide a computational complexity analysis for each algorithm.

Particle Swarm Optimization is an evolutionary population-based search method developed in 1995 by *Kennedy* and *Eberhart* [44]. PSO is inspired by the social behavior of a school of fish and flocks of birds, and it is used to solve complex optimization problems based on the movement and intelligence of swarms. In PSO, swarm members represented as particles; each particle position is considered as a candidate solutions for the optimization problem. Thus, in the initialization stage, it has a fitness evaluation (i.e., objective) function; the aim of fitness function is to evaluate the solution by assigns each particle's position to a fitness value. Each particle in the swarm keeps track to its highest fitness value; the best solution achieved by this particle is called personal best. Moreover, the particle position with the highest fitness value is called the global best. Then, the PSO iteratively improving a candidate solutions is based on the local best (*Lbest*) solutions for each particle and the global best (*Gbest*) solutions for all particles within the swarm [45].

At every iteration, the new position for each particle is computed by adding the particle's current velocity to its position. Then, each particle's velocity is modified towards its Lbest and Gbest employing Equation (32), and its new position is found utilizing Equation (33). The ith swarm particle changes its velocity $v_i(t)$ and position $p_i(t)$ at the time step t based to the following equations:

$$v_i(t+1) = w \times v_i(t) + r_1 \times c_1 \times (\mathrm{Lbest}_i(t) - p_i(t)) + r_2 \times c_2 \times (\mathrm{Gbest}(t) - p_i(t)), \quad (32)$$

$$p_i(t+1) = p_i(t) + v_i(t+1), \quad (33)$$

where w is the *inertia weight* which is a factor for the convergence behavior of the PSO since it affects the particle velocity change, r_1 and r_2 are uniformly distributed random numbers defined on the interval $(0, 1)$, and c_1 and c_2 are acceleration coefficients.

The PSO algorithm uses a clustering approach where each particle in the swarm moves towards its best previous position, called Lbest, and the global best position called Gbest. This movement is repeated until the maximum number of iterations is reached, which is the termination condition [46]. Algorithm 1 presents the pseudocode for this approach.

Basically, the proposed protocol for the clustering process can be described in two stages: (1) *cluster formation* and (2) *cluster head selection*. In cluster formation stage, the PSO algorithm is employed to produce clusters of sensor nodes with the best centroid location in which an even distribution of centroids is guaranteed across the sensor field.

Result: Set of K clusters
Input$k$: Number of resulting clusters
$\mathbb{D} = \{p_i | i = 1, 2, 3, \cdots, n\}$; n data points.
c_k: clusters centers $k = 1, \cdots, K$.
Initialization The position and velocity are randomly initialized for all particle's; c_k is randomly Initialized for all particles'; iter = iterations
for$iter = 1$ *to* max_iter **do**
for$Particle = 1$ to *total number* of *particles***do**
for$\{p_i | i = 1, 2, 3, \cdots, n\}$**do**
calculate the Euclidean distance of Ed_i for cluster center:
$$\sum_{k=1}^{K} \sum_{i \in c_k} Ed_i(x_i - u_k) = \sum_{k=1}^{K} \sum_{i \in c_k} \| x_i - u_k \|^{2.}$$
p_i is allocated to the cluster that has the nearest c_k
end
Update *Lbest* and *Gbest* values for each particle
The velocity and position are updated for each particle using Equation (32) and Equation (33) respectively.
end
end

Algorithm 1: Clustering with Particle Swarm Optimization (PSO).

In cluster head selection stage, a certain proportion of the sensor nodes closest to centroid is determined; then, the sensor node with the maximum residual energy along with minimum path loss (considering the 3D environment due to the terrain) is a candidate to be selected as cluster head. The protocol is explained as follows:

Stage 1: Cluster Formation

(1) Deploy n sensor nodes randomly within certain area with designated initial energy E_{init}

(2) Determine number of clusters K

(3) Form clusters of sensor nodes and find the centroid location for each cluster using PSO algorithm. In this context, the clustering optimization is an NP-hard problem; therefore, the results (i.e., centroids with even distribution) represent approximate solutions [43]

Stage 2: Cluster Head Selection

(1) Determine a proportion of the sensor nodes, 10% for instance, closest to the centroid. This proportion represents the candidates to be elected as CH

(2) The sensor node with maximum residual energy E_{res} along with minimum path loss will be elected to be CH

(3) The elected CH will aggregate the data from CMs and transmit it to the UAV via uplink transmission

The computational complexity of the PSO clustering algorithm depends on four steps, namely, (a) initialization of each particle with c_k, (partitioning of the data set); this requires n operations. (2) For each point in the data set, compute Euclidean distance with all centers, then assign each point to the cluster with nearest c_k (calculate partitioning quality), which requires n iterations for inner loop and p iterations for the outer loop. (3) Performs T iterations for step 2. (4) Performs p iterations to update velocity and position for each particle. Then, the worst case complexity of these steps can be expressed as $\mathcal{O}(npT)$. For constant T the algorithm complexity is $\mathcal{O}(np) \simeq \mathcal{O}(n^2)$. Moreover, the GA and PSO algorithms' complexity has been discussed in details in [46, 47].

3.2.2. Efficient UAV Placement Using Genetic Algorithm (GA). This section presents the problem of locating an efficient placement of the UAV while providing coverage for all CHs and an effective method to solve it using *GA*. This algorithm is considered as metaheuristic technique inspired by Darwin's natural evolution and natural selection theory. GA can be utilized to discover a near optimal solution for nonconvex optimization problems [48, 49]. In this paper, GA is employed to locate an efficient 3D UAV placement that maximizes the lifetime of the UAV-WSN system. Then, the GA phases is discussed [48] and how GA algorithm can be used in finding an efficient solution to the optimization problem.

GA consists of five main phases, namely, (1) initial population, (2) fitness function, (3) selection, (4) crossover, and (5) the mutation. In the first phase, a random generation process starts with a group of individuals, which is named initial population N_{pop}. Each individual describes a logical solution to the optimization problem. A group of parameters containing numerals, characters, and/or alphabets is used to represent each individual, which is called a chromosome. In this work, we represent the 3D locations (x_u, y_u, z_u) of the UAV as individuals (i.e., chromosomes). The fitness function (*FF*) represents the second phase of the GA. It determines how good the candidate's solution is. Specifically, FF is used to assess each individual in the population by computing the fitness value correlated to each individual. In every iteration, the individuals are represented by fitness scores (*FS*), which are used to describe the next generation production step. The individual with a higher FS will be

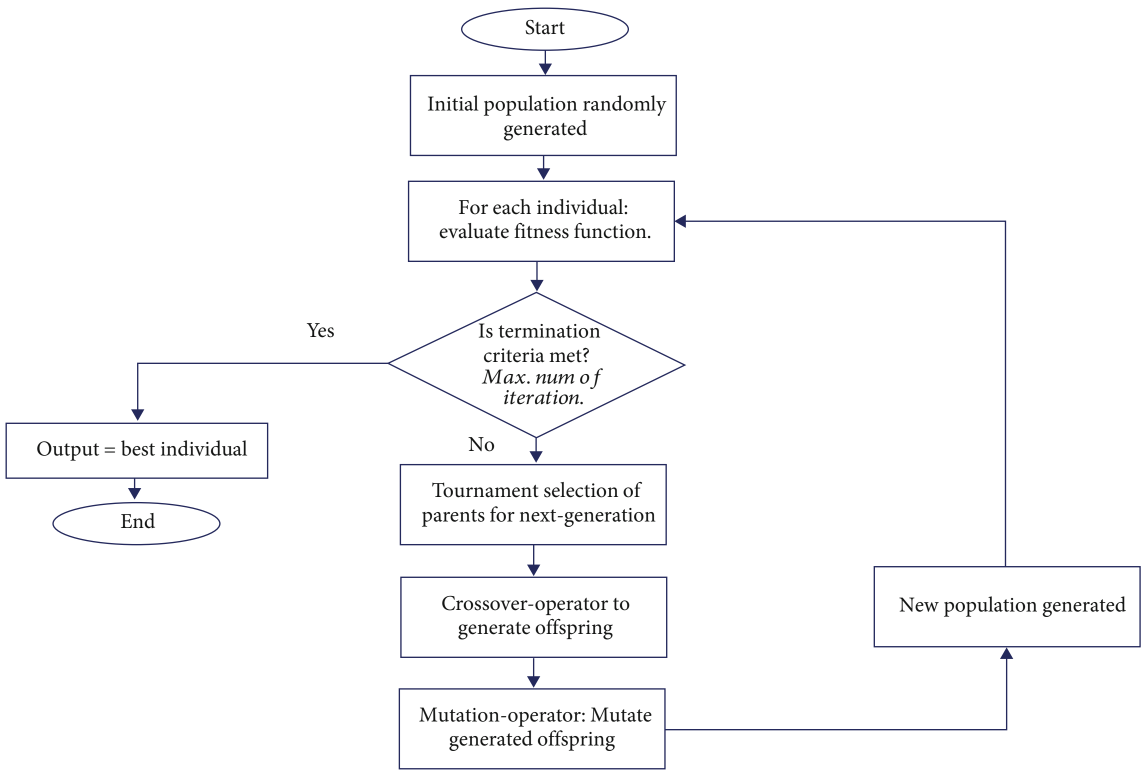


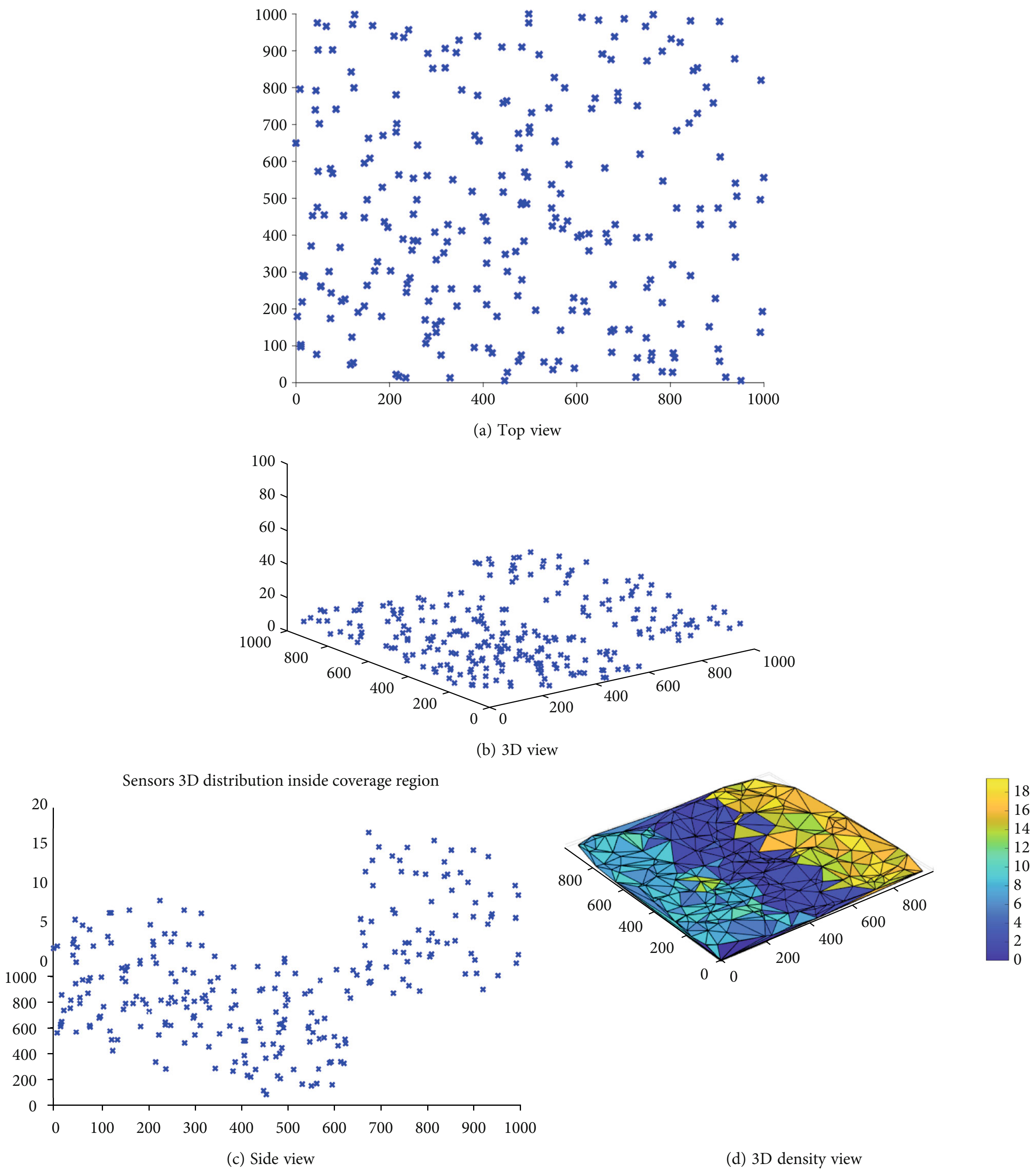
Figure 4: Genetic Algorithm flowchart.

Table 2: Simulation parameters.

Parameter	Value
R dimensions	1000 m × 1000 m
P_b	10^{-3}
$P_{\max}$	250 mW
K	1024 bit
f_c	2.4 GHz
σ^2	-120 dBm/Hz
N_f	10 dB
G_1	30 dB
M_l	40 dB
ν	3.5
η	0.35
B	1 KHz
B_u	50 KHz
R	50 kbps
τ_{th}	900 s
$\max_{\text{Alt-UAV}}$	500 m
$\min_{\text{Alt-UAV}}$	75 m
max iterations	100 (for PSO and GA)
Battery capacity	170 mAh
Battery voltage	2 volts

selected in the next phase. The third phase is the selection; this phase selects a set of individuals with the highest *FS* for generating the next generation. The third phase is the selection; this phase selects a set of individuals with the highest *FS* for generating the next generation. The selection phase is also indicated as parents. In the next generation, they inherit their genes to the offspring. This paper utilizes the tournament selection method to choose the fittest individuals from the current generation. Then, we pass on the selected candidates to the next generation. The crossover is considered the fourth phase. A crossover point is randomly selected from the genes inside the chromosome. Parents' genes are exchanged among themselves until reaching the crossover point to generate offspring. After that, the next generation is produced from the new offspring, which then will be added to the population. Finally, the mutation phase takes place in each iteration to guarantee the population's diversity and tackle the convergence to a local optimal solution. This paper utilizes a bit flip mutation operator in this phase. In this paper, the objective of the formulation problem is to find an efficient UAV 3D placement that maximizes the lifetime of the UAV-WSN system. We use the GA to find the efficient UAV placement such that the path loss value is minimized. Figure 4 depicts the flowchart of the Genetic Algorithm.

The GA complexity depends on these parameters, fitness computation function (ft), population size (P), number of generations (G), crossover (C), crossover probability (Cp), mutation (M), and mutation probability (Mp). The worst time complexity of GA is $\mathcal{O}(P * Cp * O(C) * Mp * O(M) * O(\text{ft}))$. As we can notice, GA depends on many constant



(a) Top view

(b) 3D view

(c) Side view

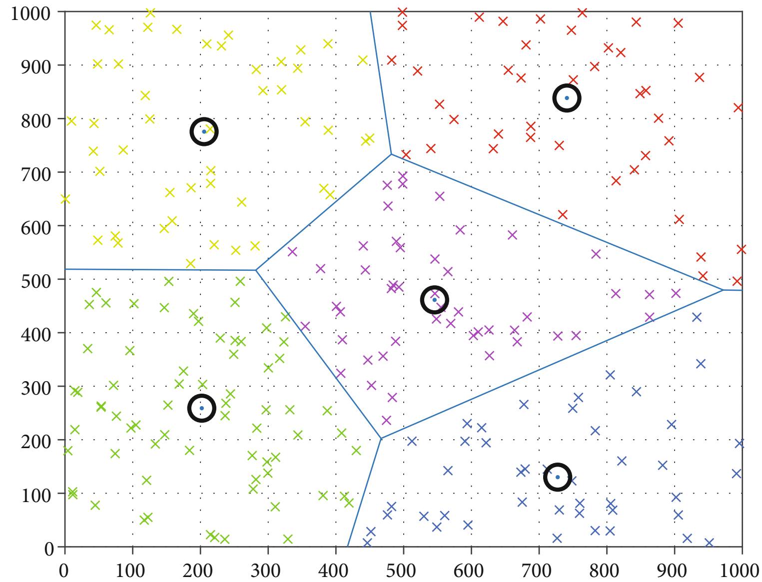
(d) 3D density view

Figure 5: Different views for the sensor nodes distributed randomly within surveillance region. Specifically, four views is presented for the distribution of wireless sensors within the coverage region.

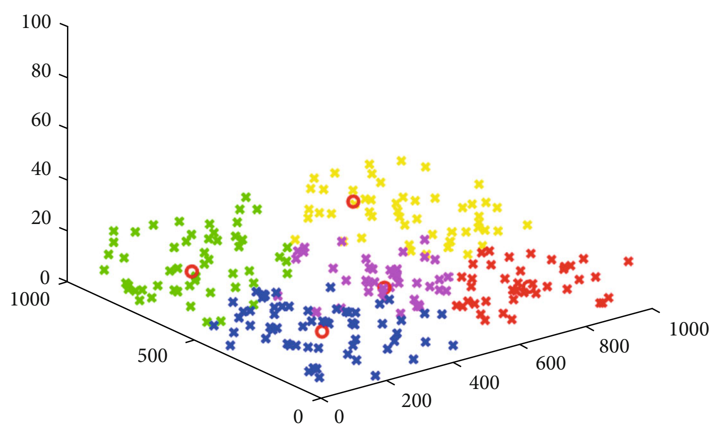
parameters, namely, population size, crossover probability, and mutation probability. Thus, the computational complexity can be simplified as: $\mathcal{O}(O(C) * O(M) * O(\mathrm{ft}))$. In GA, the fitness function requires $\mathcal{O}(n \log (n))$ time, the initial tournament takes $\mathcal{O}(n)$, and the selection takes $\mathcal{O}(\log (n))$ operations. Crossover and mutation require p times. The worst case computational complexity of the GA is $\mathcal{O}(p.nlog(n))$.

4. Simulation Results

This section presents a performance analysis for the proposed optimization framework. This analysis is demonstrated in two parts: (1) cluster-based WSN formation using PSO and (2) determine efficient placement for the UAV using GA. In this study, two main metrics are



(a) Top view for cluster-based WSN



(b) 3D view for cluster-based WSN

Figure 6: WSN clustering is performed by employing *PSO* algorithm within surveillance region. Top and 3D views clustering is shown for sensor nodes with 5 clusters using the PSO algorithm. Each cluster is marked with a different color.

Table 3: Locations for the five selected cluster heads using PSO Algorithm.

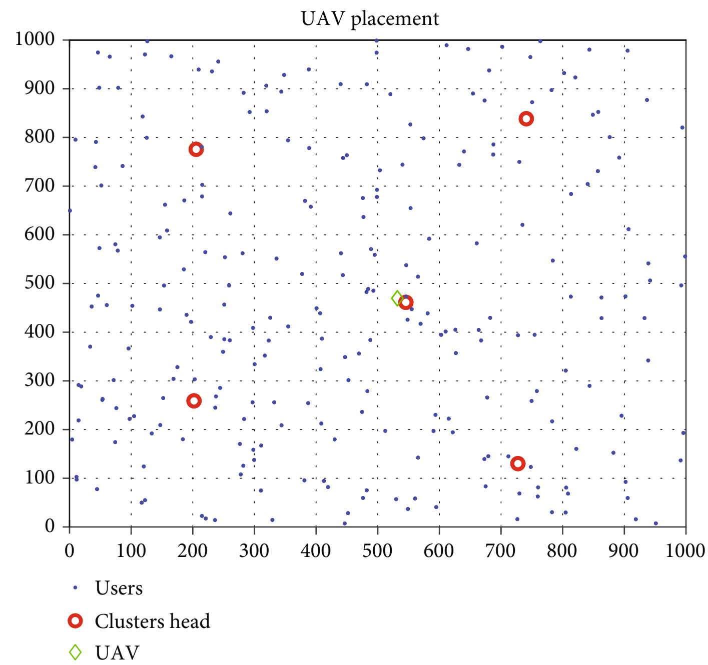
Cluster head ID	Location (x_i, y_i, z_i)
CH1	(171.97,295.72,8.94)
CH2	(211.02,769.53,4.01)
CH3	(750.41,204.26,9.89)
CH4	(486.97,392.17,6.77)
CH5	(836.46,760.89,3.99)

addressed to evaluate the performance of the UAV-WSN system, namely, (1) *Lifetime* and (2) *throughput*. Lifetime is defined as the total duration time for both CM-CH transmission and CH-UAV uplink transmission. On the other hand, throughput is defined as the total number of packets which are successfully received at UAV via uplink transmission over the entire lifetime.

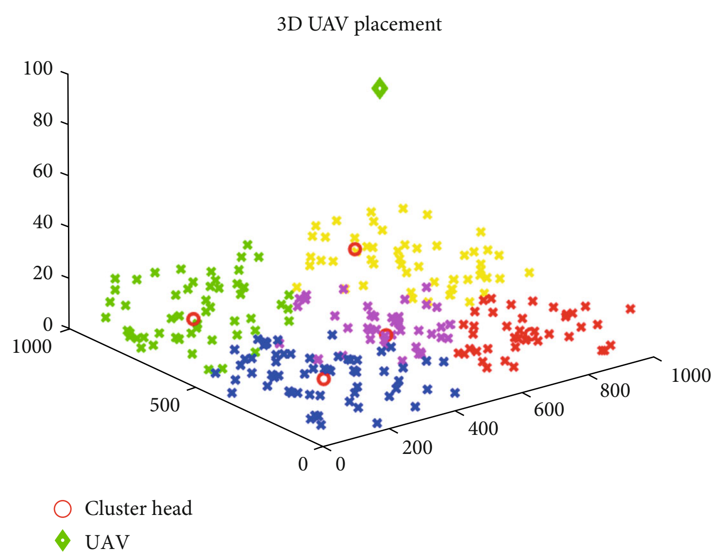
Table 2 lists all parameters that are used for the simulation. Besides, for safety reasons and to avoid collisions, in this work, the minimum UAV altitude is set to 75 m [50, 51].

4.1. Cluster-Based WSN Formation. This section presents the results for clustering the WSN using PSO. In this work, it is assumed that 250 sensor nodes are deployed randomly within the targeted surveillance region R with dimensions 1000 m × 1000 m. These sensor nodes are nonuniformly distributed based on the beta distribution function.

Figure 5 presents four views for the distribution of wireless sensors within the coverage region. Specifically, Figure 5(a) shows the top view distribution for sensor nodes, while Figures 5(b) and 5(c) present 3D and side views for sensor nodes. It is clear from these figures that the subarea has different terrains, ranging in 0-20 m elevation levels. Moreover, Figure 5(d) shows the density distribution for



(a) Top view for UAV placement



(b) 3D view for UAV placement

Figure 7: Top and 3D UAV views using an efficient placement method by employing *GA* algorithm.

the wireless sensors, the yellow gradations indicating nodes at 14-20 m elevation levels. In contrast, the blue graduations indicate an elevation level of less than 14 m.

In order to form cluster-based WSN, the PSO algorithm is employed to partition the sensor nodes into k clusters. PSO can perform a parallel and global search to find an efficient and near-optimum solution to the clustering problem. Moreover, PSO avoids the clustering problem using conventional clustering methods in k-means such as trapped into local minimum solution and can produce better symmetric clusters with equal sizes and densities. The proposed model works for any number of k clusters, as can be deduced from the input of Algorithm 1. For the scenario under consideration, the targeted surveillance region is partitioned into 5 clusters.

Figure 6 shows the clustering approach for sensor nodes into 5 clusters using the PSO algorithm. Each cluster is marked with a different color. Figure 6(a) depicts the top view for the 5 clusters and their cluster centroids, while Figure 6(b) depicts the 3D view for the clustering.

Regarding *cluster head selection*, the following steps are followed: first, for each cluster, the Euclidean distance between the cluster center (i.e., *cluster centroid*) and all sensor nodes is calculated. Then, the sensor node with the shortest distance to the centroid is selected as a cluster head. This work assumes five cluster heads with (x_i, y_i, z_i) coordinates given in Table 3.

Employing clustering method in WSNs has several advantages in terms of managing the limited energy source by controlling the topology of the WSNs. Besides, clustering

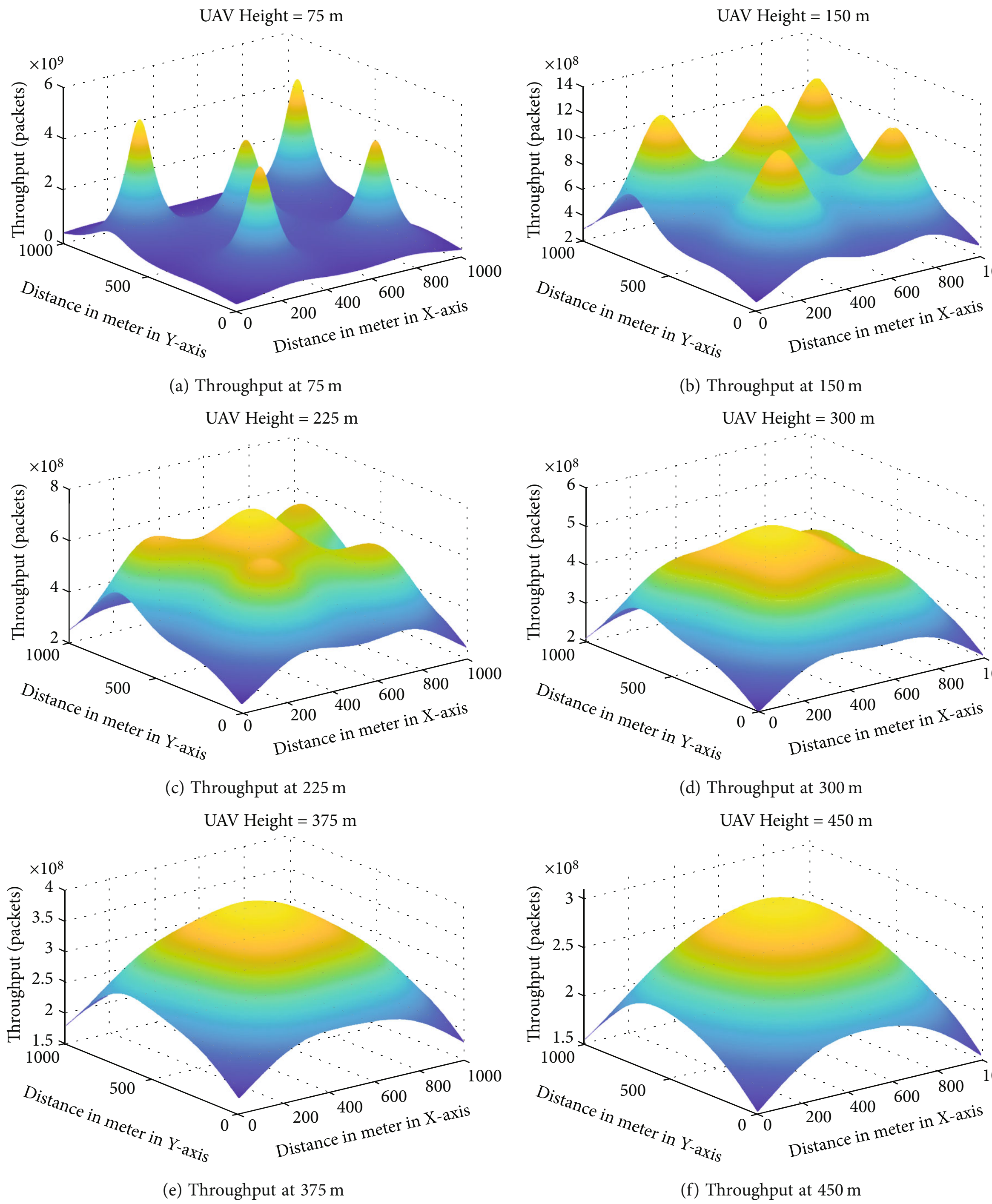


Figure 8: UAV-WSN system throughput for uplink transmission from CHs to UAV at different UAV altitudes. Specifically, the total transmitted information from five CHs to the UAV via uplink transmission scenario is presented at different UAV altitudes ranging from 75 m to 450 m.

method has a significant impact on improving the lifespan of the WSNs. Cluster-based WSN result in burden balancing among clusters where each cluster has its own duty for aggregating sensory data and transmitting it to the cluster head. Then, each cluster head is responsible for transmitting the data to the UAV via uplink transmission. The PSO ensures load balancing by approximating the appropriate centroid for each cluster. However, this process is considered as an NP-hard problem because the centroids for clusters are approximate solution.

4.2. Determine Efficient Placement for UAV. This section presents the results for efficient UAV placement using GA. The efficient 3D placement for the UAV is determined using

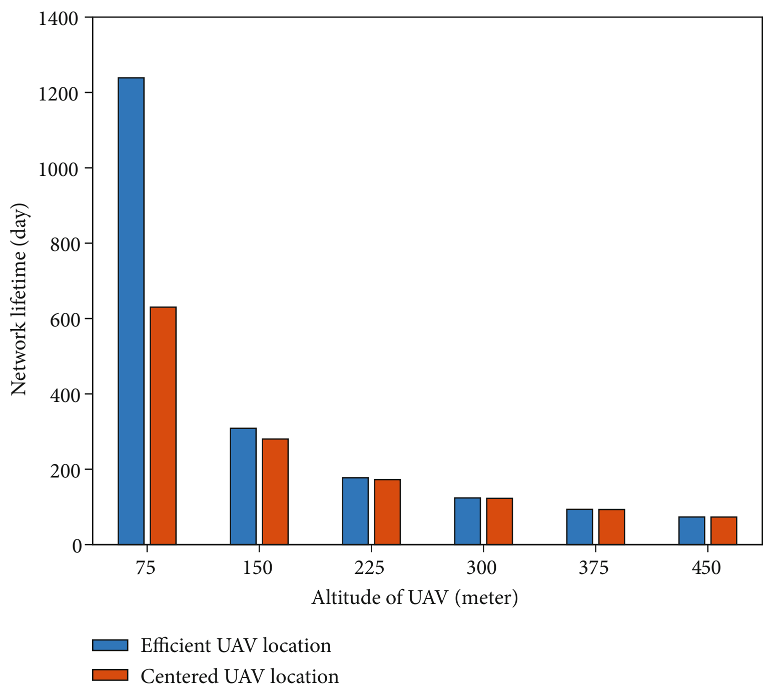


FIGURE 9: The lifetime of UAV-WSN system with path loss model based on *microwave* operating at 2.4 GHz. The results show the system lifetime at different UAV altitudes considering the two cases of UAV placement: (1) *efficient* from optimization and (2) *centered* at the surveillance region.

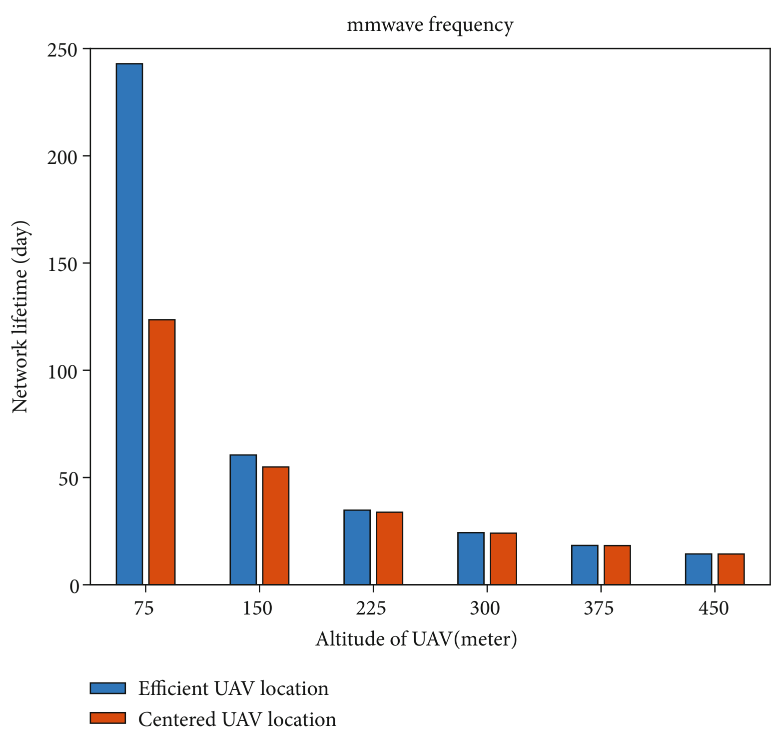


FIGURE 10: The lifetime of UAV-WSN system with path loss model based on *mmWave* operating at 5.7 GHz. The results show the system lifetime at different UAV altitudes considering the two cases of UAV placement: (1) *efficient* from optimization and (2) *centered* at the surveillance region.

Table 4: UAV-WSN system performance at UAV efficient locations.

UAV altitude (meter)	UAV placement (x_i, y_i)	Lifetime (day)	Throughput (packet $\times 10^6$)
75	(839,742)	1238.43	5200
150	(460,544)	309.03	1300
225	(456,536)	177.08	750
300	(453,521)	123.84	520
375	(456,502)	92.59	390
450	(464,490)	72.92	300

GA such that the lifetime for sensor nodes is maximized. Figures 7(a) and 7(b) present the top view and the 3D view for the UAV placement, respectively.

In the optimization problem, the goal is to find an efficient UAV placement such that the lifetime of the UAV-WSN system is maximized. Generally, WSNs are equipped with sensors to collect sensory data such as temperature, humidity, and vibration. These sensors transmit a fixed amount of information C_i several times during a day. Usually, sensors operate in two modes: active and inactive modes [52]. During the active mode, the sensors transmit the collected data to the base station while during the inactive mode, no data is being transmitted. Therefore, the power consumption in the inactive mode can be neglected. In the simulation results, we assumed each CH has a nonrechargeable battery with a capacity of 170 mAh, and the battery voltage is $V_i = 2v$, and the current I_i is variable based on the transmitted power $P_i = V_i I_i$ [53].

It is assumed that C_i is fixed for all sensors in the network; thus, the required transmit power P_i to send information with data rate C_i is given in Equation (27). The findings in this paper are presented based into two metrics: (1) lifetime benchmarks with fixed data rate C_i and (2) total information transmitted over the entire lifetime (i.e., *throughput*).

Figure 8 presents the total transmitted information from five CHs to the UAV via uplink transmission scenario at different UAV altitudes ranging from 75 m to 450 m. From Figure 8(a), we notice that at a low altitude of the UAV (i.e., 75 m), the 2D efficient position of the UAV (*according to the surveillance region*) that maximizes the total transmitted information is located at $(x = 839, y = 742)$.

On the other hand, as the UAV altitude increases, the efficient placement of the UAV approaches the centroid of the CHs (i.e., the center of the surveillance region) which is depicted in Figures 8(b)–8(f). The reason for this behavior can be explained due to the distribution of CHs over a nonflat terrain region as shown in Figure 5(d). Therefore, at low UAV altitude, the path loss distance will mainly rely on the nature of the terrain. Accordingly, as the UAV altitude increases, the effect of nonflat terrain decreases until it becomes negligible at a certain altitude. Specifically, the difference in distance between the CHs and the UAV becomes very small at high altitudes.

In other words, the GA is a metaheuristic algorithm which always searches for the optimum UAV position at (x_u, y_u, z_u). The simulation is started with minimum UAV altitude which is set to 75 m, and the GA algorithm also begins by looking for the (x_u, y_u) position on the ground. The result show that this position is not located at the center of the surveillance region which is an interesting finding, and this is because of the impact of the nonflat terrain (i.e., hilly terrain). Moreover, the simulation shows that as the UAV elevate to higher altitude, the (x_u, y_u) position on the ground converges to the center of the surveillance region under consideration. This is also another interesting finding that indicates the vanishing for the impact of the nonflat terrain because of the channel path loss and fading. Consequently, this will result in maximizing the lifetime and throughput in the case of lower altitude of the UAV; in contrast, for higher altitude, the lifetime and the throughput will decrease.

Figure 9 depicts the UAV-WSN system lifetime in terms of *efficient* UAV placement compared to its *centered* placement at different altitudes according to the surveillance area. Also, it shows that the system lifetime for the efficient placement outperforms the centered placement at the lower altitude level, while the difference becomes less at the higher altitude. Moreover, it can be noticed that as the UAV altitude increases, the lifetime decreases. The reason for these outcomes is that different terrain such as rugged hilly terrain has a high impact on the channel path loss between CHs and UAV.

Moreover, another extensive performance analysis is carried out for the proposed work. As a benchmarking, the path loss model based on *microwave* bands operating at frequency 2.4 GHz, which depicts the results in Figure 9, is compared with the path loss model based on *millimeter wave* (mmWave) bands operating at frequency 5.7 GHz in terms of UAV-WSN system lifetime. For the scenario of mmWave-based system, the results are depicted in Figure 10 and show that the lifetime decreases significantly as the UAV altitude increases for the both UAV placements: efficient and centered with better performance for the efficient placement. Generally, both results (Figures 9 and 10) are consistent and follow the same behavior; however, microwave-based system has superior performance compared to mmWave-based system.

These results can be justified based on the fact that the path loss in mmWave frequencies is generally greater than that in microwave frequencies due to the higher atmospheric absorption and scattering in the mmWave range. This higher path loss in mmWave frequencies can affect the lifetime of wireless devices in a significant way compared to microwave path loss model. Consequently, the higher path loss in mmWave frequencies can cause wireless devices to consume more power to maintain a reliable wireless link. Therefore, the increased power consumption can lead to a shorter battery life for wireless devices, especially for battery-operated devices such as IoT devices.

On the other hand, Table 4 presents the UAV-WSN system performance at different UAV altitudes and their corresponding *efficient placements* which result from the *GA* algorithm. Specifically, this table depicts the lifetime and the total throughput of the system for UAV altitudes from 75 to 450 meters. This table also shows that both the lifetime

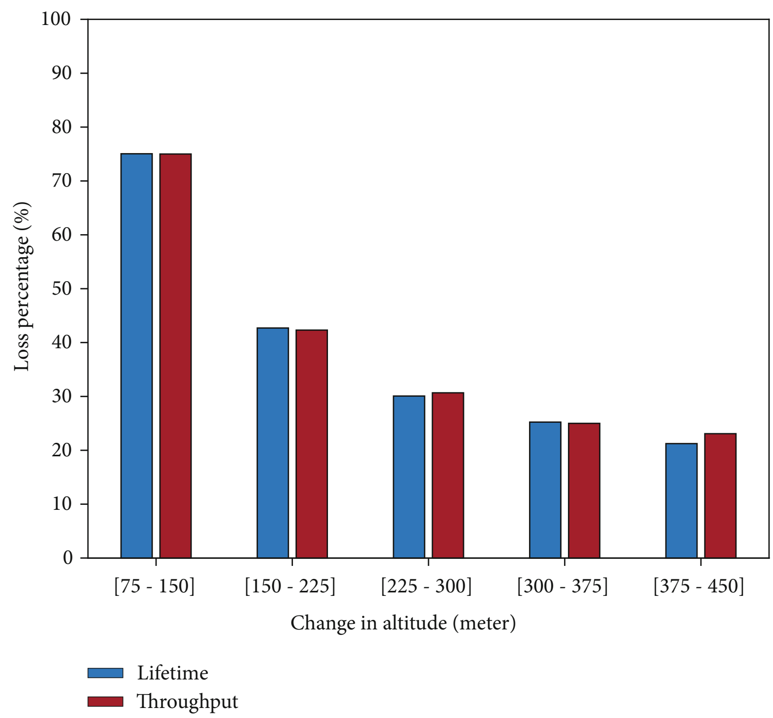


Figure 11: The loss percentage for both lifetime and altitude due to change in UAV altitude.

and the throughput are inversely proportional to the UAV altitude. Moreover, as the UAV altitude increases, the 2D coordinate placement of the UAV *converges* to the center location of the targeted surveillance region. Thereby, the change in UAV altitude will affect both the lifetime and throughput. This impact is depicted in Figure 11, where the *loss percentage* for both lifetime and altitude reach up to 75% when the altitude change from 75 m to 150 m. Also, the loss percentage decreases to reach about 21% for the lifetime and 23% for the throughput when the altitude change from 375 m to 450 m. Generally, the overall loss is about 94% when the UAV elevates from 75 m to 450 m. This finding is interesting since it exposes the significant impact of the rugged terrain on the performance of the system. Accordingly, certain settings for the system should be taken into account related to the type of terrain to achieve efficient data collection.

5. Conclusion

In this work, the limitations and challenges of WSNs in a 3D environment were addressed where scanty and insufficient sensory data is collected. Therefore, an integrated and collaborative UAV-WSN system was introduced to encounter the lack of infrastructure especially in hard-to-reach areas (i.e., hilly terrain) as well as emergency situations. Since the efficiency of the data collection is influenced by the lifespan of the sensor networks, an optimization problem was proposed to maximize the lifetime of the UAV-assisted cluster-based WSNs. This optimization study was based on two algorithms: (1) Particle Swarm Optimization (PSO) which was responsible for clustering approach in the WSN and (2) Genetic Algorithm (GA) which was responsible for locating an efficient UAV placement subject to maximize the system lifetime. The proposed study was presented in a unique way, unlike previous works. The network and physical layers were considered in the formulated problem. Performance evaluation for the proposed work was conducted and analyzed considering two metrics: lifetime and throughput. The results evinced that with minimum UAV altitude, the position is not located at the center of the surveillance region in which this case results in maximum lifetime and throughput. In contrast, as the UAV altitude increases, the lifetime and throughput decrease. Thus, the optimization formulation played a vital role in maximizing the lifetime and efficiently collecting sensory data by directing the UAV to efficient placement. On the other hand, the clustering approach demonstrated a significant effect on the lifespan and data collection at designated UAV altitudes. Moreover, the UAV-WSN collaborative system showed reliable and robust communication links between sensor nodes and UAV in the 3D regions, particularly in hilly terrain. As a result, these findings may provide outstanding guidance for the future design of these systems.

In future work, the plan is to employ multiple UAVs in the WSNs. Besides, different modulation orders will be investigated in order to study their impact on both energy consumption and throughput. Also, we intend to study the impact of different clustering techniques on the operational lifetime. This may reveal other findings related to the design of UAV-WSN systems. In addition, a future plan could be to conduct real experiments and compare their results with simulations. Also, various techniques such as collision avoidance algorithms and weather conditions will be considered.

Data Availability

Data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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