UAV-Assisted-Smart Farming for Agricultural Monitoring in a Large Scale WSN area

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Abstract

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Abstract—With the aid of multiple autonomous unmanned aerial vehicles (UAVs), data collection from the large-scale Wireless Sensor Network (WSN) is a highly efficient, but challenging solution. In this paper, to minimize the total energy consumption of both UAVs, and the effective use of sink nodes’ power, we optimize both the number of sink nodes and the trajectories of multiple UAVs in WSN. To do this, the UAV can start from the charge station and come back to the same charge station after the completion of the mission. To increase the lifetime WSN, we specifically use the Genetic Algorithm to choose the number of multiple Charge stations. Then, we utilize a Deep Q-network-based method providing a Markov decision to establish all trajectory paths. The scheduling of UAV tasks are arranged to organize the groups of charging UAVs and the number of UAVs flying to collect data. We can show that our method can expedite the process of identifying the best answers by simulating its performance and contrasting it with other traditional heuristic benchmark techniques.


I. INTRODUCTION

The use of agricultural monitoring sensors is expanding today in the framework of smart farming. These sensor nodes (SNs), which are a component of wireless sensor networks, must effectively utilize their battery power in order to gather data over a vast geographic area (WSNs). To collect data from SNs deployed over a large-scale agricultural monitoring region using unmanned aerial vehicles (UAVs), we must coordinate the UAV path by leveraging each sensor and its corresponding cluster heads (CHs). In order to optimize the UAV path across each SN and cut down on flying time, the author of just2020uav presented efficient approaches to ascertain and change the SNs’ activation times. UAVs can be used for pesticide and insecticide application, reconnaissance, and other agricultural tasks to reduce costs and advance agricultural knowledge. The author [1] identified some of smart agricultural applications, its advantages, disadvantages, challenges and limitations of UAVs including the internet of things (IOT) technology connections in a remote locations.

The limits of human demands in agriculture are now beyond the scope of today’s intelligent agricultural technology system. The soil will be negatively impacted by the growing size of the machine. The author concentrated on employing UAVs in the agriculture and agricultural production sector to increase overall production and lower overall product costs. [2]. The following are a few of the key traits of IoT and UAV-based smart farming. [3]–[5] are:-

1) Field monitoring: Through better surveillance, accurate data gathering, and data analysis, smart agriculture attempts to reduce crop waste.
2) The goal of smart farming is to locate animals that graze outdoors or in sizable stables. tracking and views: Technology also aids in evaluating the ventilation and air quality of farms and locating hazardous feces emissions.
3) Applications for greenhouses: Smart agriculture keeps an eye on local micro-climates to boost greenhouse production and the quality of fruits and vegetables.
4) Biomass management: As a preventative strategy against fungus and other microbial pollutants, smart farming helps to regulate humidity and temperature in crops like straw and grass.
5) Offspring Care: In animal farms, intelligent breeding regulates the circumstances for raising young animals and their welfare.

However, numerous difficulties impact the UAVs to better exploit the utilization of UAV-assisted data collection in a wide geographical area of WSN when several UAVs are employed to gather data in big-scale WSN. These difficulties include:

- Limited Battery Lifetime: UAVs’ performance is severely restricted by their limited battery life. Therefore, a lot of drones are only good for short-distance excursions, which greatly restricts their use. Drones need an intelligence monitoring system (IMS) to track the state of the battery and adjust their operations accordingly to maximize battery performance.
- UAVs’ may have limited communication ranges provided their nodes have fast transmission speeds, but their communication links fail to route traffic that affecting the routing mechanism.
- Management Complexity: Human UAV piloting is difficult. Manual control of drones reduces efficiency and causes inconvenience, in addition to being susceptible to human error. Insufficient physical controls, on the other hand, will result in drone crashes and damage.

The aforementioned difficulties are more focused on how to reduce operation completion times while collecting data from multiple UAVs.

In this paper, we build a multi-UAV-assisted optimization model for trajectory path planning and clustering techniques determination. The framework deploys all sink nodes and
related sensor nodes needed to collect all data throughout a sizable WSN area. Then, to reduce energy utilization, we suggest the trajectory path of several UAV algorithms. The following is a summary of the major research contributions.

- We formulate the UAV-WSN system’s overall energy consumption minimization problem by choosing sink nodes (SNs) and planning all of the UAV’s trajectories.
- In the WSN, we provide a brand-new multi-UAV assisted data collecting model. To aid sensor nodes in real-time data collection, the model can determine the best routes for many UAVs. In large-scale WSN situations based on air-to-ground collaboration, it can increase the effectiveness of data collecting. Additionally, by supplying the right amount of UAVs and sensor nodes, our model can reduce the energy consumption needed to complete the operation.
- Numerous simulations demonstrate that the number of sink nodes connected to different tiny nodes in a wireless sensor network may be determined using the genetic algorithm (GA) method (WSN). The deep Q-network-based method provides a Markov decision strategy to build all trajectory paths, while GA algorithms are utilized to determine the lifetime of network for each sink node to assess the effectiveness of a realistic solution. Our results show that the GA strategy is the best method to choose the best sink node selection algorithm.

The rest of this paper is organized as follows. Section II explains the existing research works. Section III explains all models of the system. Section IV formulates the problem in this paper. Section V propose an algorithm to solve the formulated problem. The simulation results are illustrated in Section VII. Finally, we conclude this paper in Section VIII.

II. RELATED WORK

In-depth research on drone technology and how they have changed over time in the agricultural industry is provided [6]. The use of drones for Precision Agriculture (PA), the spraying of pesticides, the design of drones, and the development of multisensor systems to innovate in certain areas utilizing various artificial intelligence (AI) and deep learning techniques have all been examined by the author. Unmanned Ground Vehicles (UGVs) operating as mobile recharging stations for unmanned aerial vehicles (UAVs) have been the subject of research by certain researchers [7]. On the other hand, a heuristic framework based on ant colony optimization (ACO) is used to solve the charging station deployment problem with a system performance is maximized to determine the ideal number and locations of charging stations [8].

Using a new, compact mixed-integer linear programming (MILP) model, the UAV route protocol planning for belt conveyor inspection is solved [9]. Sensor node with UAV capability (SN-UAV): A flat-topology routing protocol called SN-UAV addresses the issues of network lifetime and energy constraints for UAVs used as mobile data collectors for sensor nodes (SNs). High-energy dissipation can result from routing the data in a multi-hop fashion through LSNs that can stretch even up to hundreds or thousands of kilometers. A UAV-based liner sensor node (UBSN) uses UAVs to address this issue. By only taking into account a single UAV by the dock stations, the UAV-assisted intelligent transport system (ITS) for the UAV docking station placement is investigated to determine the best locations for a given number of docking stations that the operator hopes to install in a wide geographic area [10]. While planning the path of the drone using a Single Drone Multiple-Recharging Stations on Large Farm problem (SD-MRS-LF), while taking into consideration an area of interest to cover with a set of candidate locations where recharging stations can be installed on a large farm, the drone can autonomously land to recharge its battery before continuing the mission to decrease their number [11].

The author uses an artificial neural network-based response time prediction module to determine whether it is faster to complete tasks by offloading them to other drone clusters or not. This system enables a drone cluster with a high-intensity task to opportunistically borrow computing resources from other nearby drone clusters. Some authors use video data from a forward-facing camera to record the human pilot’s flight during training. The movie is used to extract several edges and gradient-related computer vision-based features. An autonomous control model is trained using the captured human-controlled inputs to link the retrieved feature vector to the yaw command. The autonomous control model is alliteratively updated using feedback from a human agent who corrects undesirable model output as part of the reinforcement learning methodology. On other hand, a thorough evaluation of the most recent embedded sensors, communication technologies, computer platforms, and machine learning algorithms utilized in autonomous UAVs is also included in certain studies. [12], [13], [13]–[16].

The aforementioned deployment of sink nodes and path planning research primarily uses a single UAV and a single planning algorithm with some traditional methods. However, in contrast to our strategy, this method is difficult to immediately apply to many UAVs in multiple trajectory path schemes. Using an enhanced heuristic GA and reinforcement learning (DQN) method, the Large-scale UAV-assisted Wireless Sensors Network may be a feasible approach to building an effective multiple UAV trajectories.

III. SYSTEM MODEL

We assume that N sensor nodes are distributed randomly over a WSN network. Sensor nodes collect several types of data that they must send to the network. When the network has to send data, the sensor nodes (n) and sink nodes (SN) are randomly positioned to perceive various types of data.

A. The Channel Model

To gather all the data and transfer it to the UAVs, sink nodes (SNs) are deployed. As a result, because they consume little power, sensor nodes (SNs) and UAVs cannot interact directly. We assume, SNs transmits its data to the associated SNs using power \( P_n \), while a K communicates with a UAV with power \( P_u \geq P_n \). In this illustration, we assume that all communications are orthogonal or that there is no interference.
Each sensor transmits its sensed data to its associated SN using power PSN, while an SN communicates with the collecting UAV using power PSN. Assuming that WSN sensors communicate with their associated SN using orthogonal channels, the received signal-to-noise ratio (SNR) at SN c for the signal transmitted by SN s, denoted $\theta_{sc}$, can be written as:

$$\delta_n = \frac{P_n D_n \alpha}{\sigma^2}, \forall n = 1, \ldots, N, \forall n' \ldots, N'$$

where, $D_{nn'}$ is the distance between sensor n and sink node $SN_{c}$, $\alpha$ is path loss-exponent, $\sigma^2$ is the noise power. We considered as the communication is successful, if $\delta_n \geq \delta_{th}$. Where, $\delta_{th}$ is the SNR threshold.

The maximum communication range for the sink node (SN) can be calculated as:

$$D_{nk} \leq D_{ntu} = \left( \frac{P_n}{\sigma^2 \delta_{th}} \right)^{1/\alpha}, \forall n \ldots, N$$

In this study, we are interested in UAVs having a communication interface. Surface $P_t R_u^2$ thus serves as a representation of the coverage. In this case, the radius of a circle with its center at the UAV projection on the 2D is $Ru^2$.

The Path Loss effect determines the quality of wireless channel flying and ground terminals (PL). The PL link from the air-to-ground terminal is a weighted combination of two links. Line of sight (LOS) and non-LOS (NLOS). The altitude of the UAV, the distance between the two transceivers, and the environment all affect the chances of obtaining a Los link between the UAV and the ground terminal.

We consider (LOS) and (NLoS) links, and the channel model does not include shadowing. The formula below can be used to determine the typical path-loss from air to ground between SN n and UAV u:

$$\gamma_u = P_{LoS}^{nu} \rho_{LoS}^{nu} + P_{NLoS}^{nu} \rho_{NLoS}^{nu},$$

where, $\gamma_u$ the average between $SN_{c}$ and UAV u ($\forall n = 1, \ldots, N, \forall u = 1, \ldots, U$) a ground terminal located at a position (($\phi c, \psi c$)) in urban environments, $\rho_{LoS}$ and $\rho_{NLoS}$ represents the probability of $LoS$ between the sink node $\kappa$ and the UAV u at position $H$. $P_{NLoS} = 1 - P_{LoS}$. And $\rho_{LoS}$ can be expressed as:

$$ln\rho_{loS} = L_{loS}(fs) + 20\log(d_n, u) + vm, \forall vm \in LoS, NLoS$$

The probability of $NLoS$ and $LoS$ depends on the environment and elevation angle which can be expressed as:

$$\frac{1}{1 + ae^{-b(\frac{\tan(\theta) - \theta}{\tan(\theta) - \theta})}}$$

where $a$ and $b$ are constants that are dictated by the environment, $\theta_{nu}$ is the elevation angle between the UAV u and sink node n in degree, $d_n, u$ the distance (in m).

$$P_{LoS}^{nu} = P_e - \gamma_u \geq P_{th}, \forall n = 1, \ldots, N, \forall u = 1, \ldots, U,$$

where PSN is the transmit power of a SN. To determine if a link is in Los or NLoS, locations, heights, and the number of buildings is required. Typically, locations and heights of buildings follow a Poisson point process (PPP) and a Rayleigh distribution, respectively. The LoS link between UAV u and SN c is blocked if it exists a building b between them such that the following inequality holds [17].

$$\frac{h_b}{\sqrt{d_{2D}^2}} > \frac{H}{\sqrt{d_{2D}^2}} \Leftrightarrow \tan(\theta) > \tan(\theta'),$$

where $d_{2D}^2$ and $d_{2D}^2$ are the projected 2D distances into the ground between UAV u and SN c and between building b and SN c, respectively, whereas $\theta$ and $\theta'$ are the elevation angles from the UAV and building top perspectives.

Some critical symbols are summarized in Table I.

### Table I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D$</td>
<td>Diameter of UAV.</td>
</tr>
<tr>
<td>$B$</td>
<td>The UAV battery Capacity.</td>
</tr>
<tr>
<td>$T$</td>
<td>Trust of UAV in Newtons</td>
</tr>
<tr>
<td>$N$</td>
<td>Number of UAVs to collect data from Cluster heads.</td>
</tr>
<tr>
<td>$D_f$</td>
<td>Drag force that depends on the air speed.</td>
</tr>
<tr>
<td>$\rho_{PSN}$</td>
<td>The power efficiency of UAV.</td>
</tr>
<tr>
<td>$PL$</td>
<td>Path loss effect.</td>
</tr>
<tr>
<td>$P_{trans}$</td>
<td>Transmission probability for one node in one frame.</td>
</tr>
<tr>
<td>$MTZ$</td>
<td>Miller Tucker Zemlin</td>
</tr>
<tr>
<td>$Ru^2$</td>
<td>The radius of a circle centered at UAV projection</td>
</tr>
</tbody>
</table>

### B. The UAV Power Consumption Model

The communication-related energy of the UAVs is listed under the power-related mounted devices in various scenarios for data gathering, but this energy is neglected in our work because it is considerably smaller than the flying motion energy. Hovering and motion power are both absorbed by the UAV while it is in motion.

1) Hovering Energy: Hovering Energy is the energy consumption of a UAV in the air when collecting data and transmitting it. The theoretical hovering power of UAV u can be calculated by:

$$p_{min}^{h} = \sqrt{\frac{T}{0.511 N D^2 \rho}},$$

where $T$ refers to the trust of UAV in Newtons, $N$ refers to the number of UAVs, $D$ diameter of the UAVs and $\rho$ is fluid density air in kg/m$^3$ respectively. The trust $T$ of UAV achieved by their induced velocity can be calculated as:
\[ p_{\text{hard}} = \frac{|P_{\text{full}} - P_s|}{V_{\text{max}}}, \]

where, \( P_{\text{full}} \) and \( P_s \) are the hardware power levels, and \( V_{\text{max}} \) is the maximum speed of UAV when the UAV, moving at full speed and when the UAV is in static mode respectively.

The motion power of a UAV can be calculated as:

\[ P_m = P_u^{\text{hov}} + p_{\text{hard}}, \]

From the above expression, The UAV flying motion energy required to move from the charge station \((c)\) to location \((n)\) can be is expressed as:

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\[ E_m(c, n) = P_m * T_f(c, n), \]

where, \( P_m \) refers the motion power of drone and \( T_{c,n} \) indicates the time needed for UAV \( u \) to fly from location \( c \) to location \( n \). According to Haversine formula, the flying time needed to fly from location \( c \) to location \( u \) can be calculated as:

\[ T_{c,n} = \sqrt{D(c,n)^2(t) + h^2_u(t)}, \]

where, \( T_{c,n} \) indicates the time needed for UAV \( u \) to fly from location \( c \) to location \( n \) referred. \( D(c,n)^2 \), refers the flying distance from the charge station \( c \) to sink node \( n \), \( h^2_u(t) \), the height of UAV to fly the given distance and \( V_n \) refers velocity constant.

The flying distance of the UAV from charging station location \((\phi, \psi)\) and the sink node \( n \) in the time slot is expressed as:

\[ D_{un}[t] = \sqrt{D_{u,\text{conv}}^2(t) + h_u^2(t)}, \]

where, \( D_{u,\text{conv}} \) is the coverage distance from UAV to sink node at the constant velocity at fixed sensor nodes, and \( h_u \) is known. The total Energy Consumption of a UAV is:

\[ E_t = \left( P_u^{\text{hov}} + P_{\text{hard}} + P_{\text{com}} \right) T_f(c, n), \]

To complete the data collection mission, the entire energy budget of the UAV on the examined path should not be exceeded by the overall energy budget of the UAV on the considered path \( E_t \). Otherwise, it is an infeasible path. This can be expressed as:

\[ \left( P_u^{\text{hov}} + P_{\text{hard}} + P_{\text{com}} \right) T_f(c, n) \leq \tilde{E}_t, \]

IV. PROBLEM FORMULATIONS

In this section, we define an optimization problem to reduce the utility function of data collection, which takes into consideration the SNs’ deployment costs and the energy used by UAVs.

In our scenario, there are some assumptions and general conditions we are considering.

- The total number of sensors is known, fixed, and distributed at random;
- The BS has an endless supply of energy and is also pre-deployed;
- After completing their mission, all UAVs recharge at the same charge stations, which have been placed;
- Assuming that all UAVs fly at the same average speed and that the hovering and flying times are fixed and sufficient to collect all data from the SN;

Our paper’s main goal is to reduce the energy consumption of UAVs and their sensors. This equation’s starting point is as follows:

(1) \[ \min_{P,S} E \]  

s.t. \[ C_{1} : (16 - 17) \]  

\[ C_{2} : W_u = \{ w_u = x_u, y_u, z_u | \forall u \in U \} \]  

\[ C_{3} : D_{\text{un}} \leq D_{\text{th}}, \forall u = 1, \ldots, N^{*} \]  

\[ C_{4} : \left\{ x_{n}^{\text{UAV}} \right\} \geq 1 \forall u = 1, \ldots, U^{*}, \forall n \in M_u \]  

\[ C_{5} : \sum_{u=1}^{U^{*}} \sum_{n=0}^{C_{nn}} x_{n}^{u} = 1, \forall j = 0, \ldots, n, j \neq n, \]  

\[ \sum_{n=1}^{N} x_{n}^{u} - \sum_{j=1}^{N} x_{n}^{u} = 0, \ldots, N, \]

where \( P1 \) represents optimization for sink node selection and trajectory length of Multi-UAV from the UAV charging station to the ending point to minimize total energy consumption. \( P, S \) represents the UAV trajectory and sink nodes are optimized in WSN respectively. Where, \( C2 \) states with \( W_u = \{ w_u = x_u, y_u, z_u | \forall u \in U \} \) is the set of ordered locations to visit by UAV u (route) to collect data from its SNs. \( w_u \) is the location in the Cartesian coordinates system. And \( \{ H_n = x_n, y_n, z_n | \forall \forall \} \) is the set of ordered locations of SNs to visit by UAV u. \( |D_{\text{un}} - D_{\text{un}}| \) is the distance between sink node \( n \) and \( c \), where \( D_{\text{un}} = 0 \), initial sink node location which is near to the charge station for all UAVs. \( X_{\text{un}}^{\text{UAV}} \) \( n = 1, \ldots, N, j = 1, \ldots, U, u = 0, \ldots, U \), with \( x_{n}^{u} \) is a binary Indicator of UAV u traveling from sink node \( n \) to sink node \( j \). \( C3 \) constraints are the budget limitations in terms of the number of SNs and UAVs. \( C4 \) and \( C5 \) guarantee the successful communications.

To solve the above issues, we consider two sub-objectives that can be distinguished: First, we formulate the WSN sensors using GA and SNs placement problem aiming to minimize the number of deployed SNs. Then, the UAVs’ path planning problem can be formulated, where the objective is to minimize energy consumption for data collection.
V. SENSORS SOLUTIONS USING GENETIC ALGORITHMS

A. Sink node selection using Genetic Algorithm in WSN

An optimization algorithm called the genetic algorithm utilizes a population of multiple solutions to find a solution to a given problem. By making various random (i.e., blind) changes to the solution in various directions, the genetic algorithm not only looks for a solution but also looks for the overall optimal solution. The genetic algorithm follows these steps to find the best solution:

1) Initialize a population of solutions.
2) Calculate the fitness value of the solutions in the population.
3) Select the best solutions (with the highest fitness values) as parents.
4) Mate the selected parents using crossover and mutation.
5) Create a new population.
6) Repeat steps 2 to 5 for several generations, or until a condition is met.

The genetic algorithm is superior to K-means for the selection problem because it is less sensitive to the initial centers. The evolutionary algorithm evolves the first solution to find the one that is globally optimal. We must consider the following things in order to use the genetic algorithm to solve our problem:

1) expressing the problem in the genetic algorithm’s dominant method, where each potential solution is a chromosome.
2) Problem encoding (binary or decimal).
3) Building a fitness function that measures the fitness (i.e., quality) of the solution.

VI. MULTI-PATH SOLUTIONS

A. DQN-based UAV trajectory planning algorithm

The above problem is the shortest path trajectory optimization problem for the multiple UAVs $Q$. Then, ensures that a UAV is used exactly once from sink nodes during data collection time.

1) Markov Decision Processes: A Markov Decision Process is a typical Markov model that has been extended, according to the source. Each state may be occupied by the set of actions that can be carried out there. The system may enter a new state as a result of these actions. The transition function $T(s, a, s')$, where $a$ denotes a movement made while the current state $s$ is present, and $s'$ denotes a new state. Using MDP, flight safety can be improved, and mission failure is less likely if a safe trajectory is created in the event of an obstacle environment.

The Markov property, which states that the probability of discovering the system in a particular state depends only on the preceding state, is a rule that all MDPs follow. As a result, the transition function and the action conducted in the preceding time step are the only factors that affect the systematic state at any given time. To enable the DQN algorithm in the proposed optimization problem, the state space, action space, and reward function are defined as follows:

1) State The state includes coordinates for all sink nodes in each cluster, the UAV’s location, and the timely completion of UAV-WSN at the current time $t$. We assume that the UAV is aware of the location of the SNs with the highest service requirement priority and set it as the target location.
2) Action The action represents the choice of the next cluster to be selected at current step $t$ and the SN in this cluster. Thus, we define the output of the right-hand side and the SN selection by DQN as the action at each step.

$$A \equiv \{a_t\} = \{ [V_x(t), \theta(t)] \},$$ (19)

The action consists of the flying speed and angle of the UAV. Both the flying speed and angle are uniformly discretized into values within their range, where $s$ is the number of degrees of freedom.

3) Reward: We design the reward as the negative of the total time minimization. This means that the DQN is set to get the maximal reward (minimal energy and time consumption). We reward the UAV based on the service requirements priority of SNs $n$ within its coverage. The service requirement priority not only considers the data buffer length and the residual battery level of the UAVs in the current slot but also takes their trend into account. The service requirement priority of SNs $n$ to upload data and charging at time slot $t$ are defined as $Q^d(n,t)$ and $Q^e(n,t)$ respectively can be given as:

$$Q^d(n,t) = \Pi(n(t)) \frac{b^d(n,t)}{b^d_{max}(t)},$$ (20)

$$Q^e(n,t) = \sum_{n} \frac{b^e_{max}(t) - b^d(n,t)}{b^e_{max}(t)}.$$ (21)

DQN-based Algorithm for Trajectory Planning

1) Initialize the action-value function $Q$ with the random weight $\theta$;
2) Initialize the target action-value function $Q$ with weight $\theta' = \theta$;
3) Initialize replay buffer $B$ to capacity $N$;
4) Initialize $\varepsilon$ for action exploration;
5) for episode $i = 1,\ldots,K$ do;
6) Initialize the environment and receive initial state $s$ according to (22);
7) for $t = 1,\ldots,T$ do
8) Update the system status according to (18) and record $G_d(t)$, $G_e(t)$;
9) With probability $\varepsilon$ select a random action $a_t$; if $a_t$ will lead the UAV fly out of the designated area; then
   $$a_t = [0,0], G_f(t) = 1;$$
end if
10) Execute action $a_t$, observe reward $r_t$ according to (21) and observe new state $S_{t+1}$ accordingly;
11) Store transition $[S_t, a_t, r_t, S_{t+1}]$ in $B$;
Fig. 2. The flow chart of GA in large WSN area.

12) Randomly sample N transitions from B;

13) Train the network and update parameters $\theta$ using gradient descent;

14) Every K steps update $\theta' = \theta$;

15) \textbf{end for}

16) \textbf{end for}

VII. PERFORMANCE EVALUATION

The simulation for the Python-based sink node selection algorithm and the WSN path planning algorithm is done in this section. We discuss various UAV counts’ sensing and communication skills. When calculating simulation performance, the following elements are taken into consideration. Begin counting each item On figure 3, we simulate the number of all nodes that are randomly placed in a large WSN geographical area using a genetic approach.

1) The number of sink nodes in Figure 3 is selected with an appropriate placement for all UA Vs using a Genetic Algorithm to collect all the data from them.

2) The performance of each method is examined in Figure 4.

3) Figure 5 illustrates how each UA V’s trajectory is made to consume as little energy as possible using DQN and other benchmarks.

Figure 2 displays the flowchart of the proposed genetic algorithm (GA) algorithm to determine the sink nodes, which are associated nodes in the WSN for UAV, from which a given number of sensors are randomly picked. In the coverage region, which must be close to sink nodes $= (\phi_1, \psi_1)$, the installation of the UAV charge station is already complete. Due to GA's simplicity in comparison to other heuristic algorithms with a limited number of numerical parameters, we implemented it.

We represent Figure 3 in GA using a charge station site with better coverage 1. The fleet of UA Vs departs from this charge station, which is located from the area’s geographic center and returns there after completing their tasks. We used the same region for the GA algorithm, and all of the places in the region have high fitness levels without any varying environmental factors. Initial charge station, which is close to the sink node, is where all UAVs take off from.

In Figure 4, we assumed that a WSN covered a large geographic area and had N nodes placed in a randomly created sensing zone, defined by area A. In an intelligent management system (IMS), multiple UA Vs are utilized to gather information from SNs connected to nodes N to get around problems with communication distance. The WSN's scalability is ensured by the sink nodes (SN), which are bid read lines in each of the small nodes in Figure 3 and can handle enormous amounts of data. In addition, sink nodes can have their data loads balanced among them to increase their availability in WSN by deploying and distributing sink nodes.

The limitations can be utilized to reduce the energy consumption of the three UA V groups in a specific dock station such that every site is covered by UAVs, as shown in Figure 5. When we contrast the lengths covered by UAVs that are either hovering directly above the SN or just flying a few short kilometers from each SN that is home to sensors. In our situation, the UAV hovering close to each SN reduces the distance traveled and the duration of the data collection operation. In our scenario, the proposed DQN algorithm with
other benchmark algorithms, $0.60\%$, PSO = $0.35\%$ and ACO = $0.2\%$ performance. Therefore, DQN is the best solution for the trajectory path in the given algorithms.

VIII. Conclusion

In this article, we presented the UAV-Assisted WSN framework, which sought to gather data across the shortest trajectory and for the least amount of energy cost. To increase the sensor life, the sink nodes in the WSN are arranged using the heuristic GA. Using the reinforcement learning (DQN) method, which is utilized to obtain UAV flight paths, we attempted to solve the optimal and best path. Finally, in big WSNs, the incorporation of trajectory fairness is advantageous.

Acknowledgment

A preprint has previously been published [18]” and then a reference to the preprint should be included in the reference list.

References


