Received: April 18, 2023. Revised: July 14, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Reinforcement Learning-based Topology-Aware Routing Protocol with Priority Scheduling for Internet of Drones in Agriculture Application

Ali Hamzah Najim[1] **Ali Hashim Abbas**[2]* **Kareem Al-sharhanee**[3] **Hussein Muhi Hariz**[4]

[1]*Department of Computer Technical Engineering Imam Al-Kadhum College (IKC) Al-Diwaniyah, Iraq, 58001*
[2]*College of Information Technology, Imam Ja'afar Al-Sadiq University, Al-Muthanna, 66002, Iraq*
[3]*Department of Communication Technical Engineering,*
College of Engineering Techniques Al-Farahidi University Baghdad, Iraq
[4]*Computer Engineering Department, Mazaya University College, Nasiriya 64001, Iraq*
* Corresponding author's Email: alsalamy1987@gmail.com

Abstract: Internet of drones (IoD) are commonly constructed with unmanned vehicles, have been progressively prevalent due to their capability to operate quickly and their vast range of applications in a variety of real-world circumstances. These IoDs are interact with zone service providers (ZSPs) to achieve the goal of assisting drones in accessing controlled agriculture services. The utilization of drones in precision farming has lately gained a lot of attention from the scientific community. This study addresses with the assistance of drones in the precision agricultural area by analysing communication protocols and applying them to the challenge of commanding a fleet of drones to protect crops from parasite infestations. objectively and equitably assigns a weight to multiple service scheduling parameters based on maldistributed decision making theory, calculates the serving priority of each service request group, and then serves the service request groups based on the calculated serving priori-ty accordingly Hence, this paper proposes reinforcement learning-based topology-aware routing protocol with priority scheduling (RLTARP) to provide reliable combinations between the source and destination. It also improves the routing decision by considering two-hop neighbour nodes, extending the local view of the network topology. The priority scheduling method adopts maldistributed decision making theory, to find the group of priorities based on service request. The proposed RLTARP is compared with three existing methods such as DroneCOCoNet, Markov decision process (MDP)and deep deterministic policy gradient (DDPG) and hence it produces 46.34% of packet delivery ratio, 67.49% of end to end delay, 16.45% of routing overhead, 13% of energy consumption and 97.6% of network lifetime.

Keywords: Internet of drones, Reinforcement learning, Routing process, Decision making, Agriculture.

1. Introduction

All Since they were first used in 1980, unmanned aerial vehicles (UAVs) have been put to a wide variety of purposes. The drone throughout agriculture seems to be a feasible option to meet the requirement of enhanced populations and food manufacturing because of their improved precision, reliability, and capacity to overcome huge barriers that conventional equipment cannot. This sector would be greatly improved through precise measurements, actual data collection, and improved agricultural management [1]. Different IoT technologies can be included into agriculture drones to benefit the agricultural business as IoT becomes increasingly industrialized. Drones are more user-friendly, effective, and capable of being piloted by landowners for collect precise, actual information. Improved effective crop maintenance can feasible by localizing, analysing, and interpreting the elevated images taken by the drone [2]. The relevant studies of comparable aircraft have been discussed in this research along with potential fixes. Some few suggested methods have been provided that could be combined with Microprocessor to produce better aircraft for agriculture [3] employing the most effective and appropriate equipment. With a reliability of 79% and 66%, correspondingly, aerial photographs are employed for purposes including recognizing sparse shrub lands and grassland for degradation surveillance. Nevertheless, drone should be deployed in order to meet the demand for smart agriculture. When they get nearer to the ground, the drones deliver precise data on the ground and increasingly accurate images [4]. Drones could be adjusted and utilized to measure distances out from ground, depth levels, agricultural water stress levels, physiological properties of crops, and many other things. Thus, effective, precise cultivation is made feasible by an aircraft that is appropriately outfitted with necessary equipment and technologies [5]. Remotely sensed equipment, including spacecraft and UAVs, are used to identify the presence of bugs and pests on fields in order to discover carnivorous bugs and rapidly alert landowners towards the issue. The advantages of elevated technology for remote sensing for agriculture include a wide monitoring region, precise sensitivity, a short returning interval, & inexpensive budget. On the one hand, a satellite device might cover a wide area and therefore is helpful for a range of catastrophe surveillance [6]. Contrarily, space monitoring can weather-sensitive and has a lower density, which makes it much more challenging to meet this need for insect monitoring in agricultural fields [7]. Unmanned aerial vehicle (UAV)-based recognition methods, some-times referred to as low-altitude remote location technologies, are currently widely employed in contemporary sectors and guarantee excellent data accuracy. Agricultural illnesses and infestations surveillance should be regulated and computerized whenever drones are employed to detect the presence of bugs and pests. However, a drone on a distant vast field must deal with problems including a limited travel time and frequent charge changes because of its limited transporting capacity and memory [8]. It is becoming increasingly popular to utilize training techniques to improve information retrieval from sensory information. Regrettably, such methods have trouble in handling different biological shapes and may require extensive training. Researcher gathered a semi-machine learning method that would combine human computer data to train from blended human Parasite plantations [9].

1.1 Contributions

1- To solve the localization with current position-based routing protocols in IoDs, researchers suggest a reinforcement learning-based topology-aware routing protocol with priority scheduling (RLTARP).
2- The priority scheduling method adopts maldistributed decision making theory, to find the group of priorities based on service request.
3- Service scheduling model is applied to service calls for both downloading and uploading.
4- To maintain the overall topology among UAV nodes for predicting the best route using various metrics.

1.2 Paper organization

The structure of paper is as follows: A relevant collection of research for IoDs for smart farming and agriculture is provided in section 2 of the presentation with table. In section 3 suggested reinforcement learning model is given. In part 4, the performance of the suggested model is shown along with a benchmark method. section-5 gives the conclusion.

2. Related works

Machine learning has made it possible for data analysis in the number of disciplines of agro technology, that has benefited from the development of big data innovation and knowledge computers. Throughout this article, scientists provide a thorough evaluation of research on machine learning models in agro ecosystems. The smart irrigation system in [10] uses models to determine the quantity of water a crop will need. It consists of heating rate, moisture, and pressure sensor that are placed in farm areas and transmit data through a computer chip to create an IoT system with data centre. To effectively forecast outcomes, the decision tree method, an advanced machine learning technique, was used to gathered information.

According to [11], decision-making systems that use artificial intelligence could improve the advantages of smart agriculture. In terms of controlling micro-nutrients, computer vision plays a crucial role in agriculture. Under [12], the authors present a cutting-edge "DroneCOCoNet" system for aerial footage analytics which organizes smart analysis of massive video collections via edge cloud computing and carries out internet protocol allocation using resource awareness. They offer 2 techniques for outsourcing peripheral calculation: heuristic-based and reinforcement learning-based methods. Such strategies offer clever job communication and collaboration for dynamic decision-offloading amongst UAVs.

A unique crossover choice technique using deep reinforcement learning (DRL) was presented within [13] with the goal of preventing pointless transitions whilst preserving stable communication. The suggested DRL framework creates a received signal strength indicator (RSSI) cantered on an optimization method for the digital training of UAV turnover choice and uses the UAV environment as just an inputs for a localized strategy evolutionary algorithms. In [14], two deep reinforcement learning algorithms are put out to handle the optimization problem of maximizing the whole network sum-rate along with a Markov decision-making process.

Using the UAV's starting spot and the destination device, [15] employed the deep deterministic policy gradient (DDPG) approach that create the optimum design for the UAV inside an extra hurdle context. In [16] the author made suitable for low resource usage, a pervasive farming mobile sensor network-based threshold built-in MAC routing protocol (TBMP) has been developed.

Mobility management UAV-based grouping (MMUG), for the transfer of bio-logical data through one base station to another via UAV, was proposed in this study ([17]). Using the cluster head's service area, the UAV develops the clustering structure. The node closest to the base station is chosen by the cluster head. It continuously tracks the movement of UAVs within its coverage area, which con-tributes to the reliability of the connection.

Using a drone to float over the IoT devices and gather data, [18] provides two route strategies for data gathering in WSN. Every sensor node is assigned a weight based on its importance during the data collection process. The drones would choose the node with the biggest weight while choosing its ultimate destination. Utilizing the data distributed by the sensor nodes in WSN, using the optimized link state routing (OLSR) method, researchers had built parameter estimators. With Smart crop monitoring in consideration, an appropriate adaptation to the routing protocol for low power and loss networks (RPL) has already been suggested in [19]. The suggested improvement proposes an energy-efficient unique cluster - based routing topology.

Table 1. Comparison of various existing methods

Ref.	Method	Merits	demerits
[10]	Decision tree algorithm	Reduced inefficiency due to highly controlled flooding	In comparison to other protocols, there is still a large latency.
[11]	decision making system	Accelerate the rate of received packets	Minimal recovery plan
[12]	DroneCOCoNet	increased scaleability	There is no substitute to ensure information transmission.
[13]	Deep Reinforcement Learning	Increase the rate of packet transmission	network's latency is more
[14]	Markov decision process	Boost packet arrival rates for systems with few connections.	ignores the time till the connection expires
[15]	deep deterministic policy gradient	Ease traffic	restriction based on an application
[16]	threshold built-in MAC routing protocol	Increase the rate of data packets	the network's latency is huge
[17]	Mobility Management UAV-based Grouping (MMUG)	capable of managing costs	delay in function
[18]	optimised link state routing (OLSR) protocol	lower price	It requires time.
[19]	hierarchical routing structure	It brings down variability.	intricate connection

3. System model

IoDs, which are connected with sensors, were developing into strong detecting systems that enable IoT-based methodologies. The sensors' job is to take pictures with a superior spatial and temporal resolution, that can help with monitoring a variety of vegetation-related traits. According upon the various agricultural factors that must be observed, as illustrated in Fig. 1, various types of sensors can be utilized in an agricultural IoD.

In this investigation, N low-altitude UAVs or drones are taken into account, and their index sets are denoted by $X = \{1,2, \dots x\}$. UAVs are used in the sensing of a surface area for observation operations and are outfitted with GPS, inertial measurement units (IMU), cameras, sensors, and a wireless communication interface. It is assumed that all UAVs are randomly distributed in a 3D space. With a shared constant transmission range R at each station, each UAV may detect a region. By

Received: April 18, 2023. Revised: July 14, 2023.

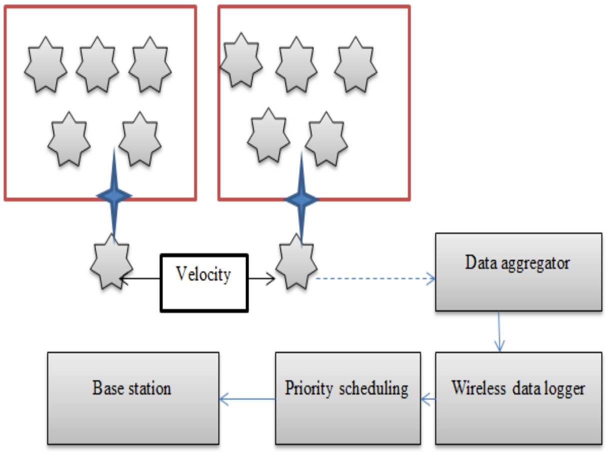

Figure. 1 System architecture for IoD deployment and message transmission in network

employing GPS, each UAV is aware of its current location(a, b, c). The BS, which is regarded as the destination of the data packets, receives the data from UAVs that monitor the region and collect photos and video from the surveillance area. UAV node $i \in X$ location data and transmission power are shown as $t_j = (a_j^{uav}, b_j^{uav}, c_j^{uav})$ and Q_i, correspondingly. Let's describe the network model as $G = (X, R)$,, where X is the set of UAV nodes and $R = \{r_1, r_2, \dots r_n\}$ is the set of UAV node positions, taking into account all UAV placements and transmission powers. We take into account the forwarding path of N number of UAVs for collision-free paths. Suppose that location parameters of UAV network i at time, $\forall i \in \{1, 2, \dots, N\}$, $t \geq 0$ are as follows: $r_i\,(t) = (a_j^{uav}(t), b_j^{uav}\,(t), c_j^{uav}\,(t)$. In order to prevent collisions between two UAVs, a minimum distance d_min is necessary. The following need must be met in order to entirely prevent a collision involving two UAVs. The preceding prerequisite should always be met in order to fully prevent a difference between two UAVs:

$$r_i(t) - r_j(t) \geq d_{min}, for\ all\ i \neq j, t \geq 0 \quad (1)$$

With this scenario, the UAVs modify its height to prevent a conflict whenever 2 of them are less than or equivalent to d_{min}.

3.1 Channel model

Both of the doppler effect of the UAV flying and the micro-doppler effect of the UAV movement must be accounted for while simulating the route. Additionally, reflection between UAVs should be taken into account in the situation of multi-UAV interaction. The UAV's cruising route could be a straightforward circular with a circumference of [20]

$$Rad = \frac{Vel^2}{11.26 \times tan(\theta)} \quad (2)$$

R stands for radius in feet, Vel for speed in knots, and θ for bank angle. A UAV with >150 per kg extra capacity must maintain a top speed of 200 mm (14.4 knots). The complicated value network coefficient of the wireless medium here between receiver and the transmitter can be described as follows for the spectrum non-selective wideband transmission medium:

$$\sigma = \sqrt{\rho(d)\delta'} \quad (3)$$

Where $E[\delta'^2] = 1. \delta'$ is typically equal to 1, and $\rho(d)$ is a complicated nonlinear function that reflects the large-scale path loss. The tiny attenuation due to multipath channels generated through other UAVs the uplink route loss is thus provided:

$$\varepsilon = \rho(d). \alpha \quad (4)$$

Regardless of whether the transmitter and receiver are placed equally apart, the route loss between them may change because of possible changes in climate. A common model for is the log-distance path-loss (Pat_Loss) concept $\rho(d)$ is given as

$$Pat\_Loss_{LD}(d)[dB] = Pat_{Loss_{LD}}(dist_\theta) + 10nlog(\frac{dist}{dist_\theta}) \quad (5)$$

Where in d is the 3D radius in metres and $dist_\theta$ is the standard length of the free space route loss (from the broadcast ends to the receivers). It is necessary to precisely determine "$dist_\theta$" in various propagation conditions.

3.2 Reinforcement learning for IoD

Throughout this subsection, we construct the control system problem in IoD networking for sensing application. N drones are used to gather data, that is then transmitted to the IoT Infrastructure for additional operations. In order to meet the QoS criteria and reduce the average system electricity costs across all drones, the issue is then stated as

$$P_0: min = \frac{1}{t}\sum_{t=1}^{\infty} E^{sys}\ (t) \quad (6)$$

 DOI: 10.22266/ijies2023.1031.34

Obtaining global optimality at every period necessitates full knowledge of many epochs (i.e., both the past and the future iterations), as they are interconnected via each drone's battery level status and energy usage. In order to create decisions through interacting with the environment, we therefore need the reinforcement learning method. In order to reduce the cost created, reinforcement learning specifically maps the environment states to the best way to proceed by the active learning.

3.3 Reinforcement learning-based topology-aware routing protocol

Throughout this subsection, designers introduce the RTARP in IoDs reinforcement-learning routing technique, which helps to enhance the AODV protocol. AODV, nevertheless, can't be used in IoDs because it ignores the special characteristics of these systems, such as highly mobile UAVs and frequent disconnections. Therefore, we work to make this routing protocol better so that it may be used with IoDs. To develop stable paths with low delay and increase the packet delivery rate, RTARP takes into account a variety of factors, including link quality, movement orientation, path latency, location between nodes, and energy (PDR). Two components make up RTARP: 1) Route finding 2) Routing upkeep. The following provides element examples of each part.

3.4 Two-hop neighbor discovery

In RTARP, a source node so_{node} looks up a reliable path in its routing table when it wishes to establish a connection link with a destination node des_{node} for exchanging data packets. When a valid path cannot be found among a node itself and, reinforcement learning-based routing is used to find the best route, or b_route, to exchange data packets. Each flying node, or fly_{node}, in this procedure exchanges Hello messages with its surrounding UAVs on a regular basis. This notification includes the following data: spatial information (a_i^t, b_i^t, c_i^t) angular velocities $(vel_{x,i}^t, vel_{y,i}^t, vel_{z,i}^t)$, at the period interval, delay information, reinforced-value, and energies $(ener_i^t)$. An adjacent table is where fly_{node} maintains information about its neighbours. fly_{node} computes the filtering parameter fil for each nearby node using data from such table, as in $fly_{node(neigh)}$. This option enables the fly_{node} to select out some of its neighboring who are unsuitable for RREQ rebroadcasting and add additional competitors to a list of permitted neighbours $license$. fly_{node} uses 4 factors for calculation, comprising movement direction and speed.

- Motion direction $\delta_{a,b}^t$: fly_{node} computes the angle between itself and $fly_{node(neigh)}$ at time t. Fly node tends to increase fil pertaining to $fly_{node(neigh)}$ to gain a higher chance of being placed in license D since the interaction link between fly_{node} and $fly_{node(neigh)}$ is legitimate for a prolonged period of time if the motion orientation of pair of nodes is comparable (i.e. the angle between fly_{node} e and $fly_{node(neigh)}$ is zero. As a result, more stable routes are built. The ratio here between movement orientations of between fly_{node} e and $fly_{node(neigh)}$ is determined by the equation following.

$$\delta_{a,b}^t = cos^{-1} \frac{vel_{x,j}^t vel_{x,i}^t + vel_{y,j}^t vel_{y,i}^t + vel_{z,j}^t vel_{z,i}^t}{|vec_i^t||vec_j^t|} \quad (7)$$

Where ($(vel_{x,j}^t, vel_{y,j}^t, vel_{z,j}^t)$ and $(vel_{x,i}^t, vel_{y,i}^t, vel_{z,i}^t)$ are, correspondingly, the acceleration matrices of fly_{node} and $fly_{node(neigh)}$. Additionally, the vectors' lengths are indicated by $|vec_i^t||vec_j^t|$.

- Distance $dis_{i,j}^t$: fly_{node} raises the fil equivalent to $fly_{node(neigh)}$ if the proximity between it and its neighbor, such as $fly_{node(neigh)}$, is appropriate. As a result, $fly_{node(neigh)}$ has a higher chance of having a license. The appropriate distance denotes that fly_{node} and $fly_{node(neigh)}$ are not located close to one another because if fly (node(neigh)) is chosen as a relay node, the path's hop count will increase, making it harder for fly node to locate the path. The appropriate proximity, on either contrary, indicates that fly_{node} and $fly_{node(neigh)}$ were not very far from one another these two nodes swiftly leave each other's transmission distance. As a result, the path that these nodes generated will shortly become invalid. $dis_{i,j}^t$, also known as the appropriate distance between the two nodes, lies between D_{min} and D_{max}, where $0 \leq Dis_{min} < Dis_{max}$ and $0 \leq Dis_{max} \leq Rad$. Rad represents the network's UAVs' broadcast range. fly_{node} and $fly_{node(neigh)}$ can provide stable pathways in this situation. It's important to note that this teaching

Received: April 18, 2023. Revised: July 14, 2023.

$$Reward\ (n_1, a_1) = \begin{cases} R\_\max & node_{t+1} is\ destination \\ R\_\min & node_{t+1} is\ local\ minimum \\ (1 - \frac{rou_{time}}{\max(rou_{time})} + \left(1 - \frac{h_{cou}}{N-1}\right) + fit_{rou}, otherwise \end{cases} \tag{8}$$

approach considers the networking to be the environment. The flying node (also known as the fly_{node}) that has obtained the RREQ message is represented by the state of the agents. The activity throughout this procedure stands for a collection of nearby nodes that are permitted to receive RREQ messages in their current states (i.e., $fly_{node(neigh)} \in license$). This set's representation is $A = \{fly_{node} \rightarrow fly_{node(neigh)} 1, fly_{node} \rightarrow fly_{node(neigh)} 2, \dots fly_{node} \rightarrow fly_{node(neigh)} K$. When the RREQ message, the agent, is in the state fly_{node} i and performs the action, the state is changed to $fly_{node(neigh)}$. Researchers establish various reinforcement learning elements, such as the learning rate (α) , discount factor (γ) and reinforced value, when the path discovery procedure is first started. While transmitting RREQ from the so_{node} and des_{node} , the suggested learning model should optimize the payoff. In RTARP, we take into account three balances: route time rou_{time} , hop count (h_cou), and route fitness (fit_rou .). The function that rewards finding the optimum path ($\_PATH$) for transferring data packets between the so_{node} and des_{node} . The path with the highest fitness, the fewest hops, and the shortest delay is called Best Route. As a result, the compensation function is determined using Eq. (8)

The objective of the route scheduled maintenance is to quickly identify a broken route and substitute it with a fresh way for data packet transmission. The constructed route must be modified if one of the following mechanisms is present to prevent failure:

- **Phase 1:** Whenever a fly_{node} is in the process of dying in a path, which occurs whenever the vitality level falls below the $ener\_th$ energy threshold (i.e., $ener_{fly_{node}} < ener\_th$). Therefore, since fly node cannot complete the data transfer procedure, this pathway must be changed.
- **Phase 2:** The buffering capacity is in the overflowing state whenever the traffic level of a fly_{node} in one path exceeds the traffic threshold tr_th (ie., $tr\_fly_{node} > tr\_th$), As a result of the path being blocked, there is an extremely significant delay when data is transferred along it. As a result, since this path is unable to transmit packets of data, it needs to be changed.
- **Phase 3:** fly_{node} and $fly_{node(neigh)}$ connector is breaking in mode 3 whenever it falls below grade threshold q_th, indicating that the relationship quality is poor. Consequently, this course has to be changed.

The compensation associated with fly_{node} will be equal to R_{min}. if any one of the three modes happens. fly_{node} next looks through its forwarding table to discover the pathways which involve it. A return message with the satisfaction is sent by the fly node to the networks it has come before. In order to select a different UAV as the next-hop location and alter the path, the preceding station subsequently runs the reinforcement learning algorithm. Keep in mind that till the new path is found and updated, the old route is still valid and can be used to send data packets. Data packets are moved onto the new path after that the old path has been eliminated.

Step-1 establish the connection between so_{node} and des_{node}
Step-2 check for the valid path
If it is found then exchange the packets
Else, revalidate the path
Step-3 send the notification message
Step-4 adopt the fly_{node}
Step-5 compute the distance between fly_{node} and $fly_{node(neigh)}$
Step-6 computes the radius
Step-7 calculate route time rou_{time}, hop count (h_cou), and route fitness (fit_rou)

3.5 Priority scheduling service

As upload requests and download service requests start competing for the same minimal interaction channel capacity, if the agriculture zone (AZ) is unable to fulfil a few posting service requests, a few data could not be timely up to date and download service requests may receive stale data, which lowers the quality of data service as a whole. In order to maximize the benefits of event schedule via combining the supplied download and upload service demands, it is crucial to create a service request balancing scheme. Assume that the communication throughput for upload requests is allotted at, δ and the remaining bandwidth, rest $1 - \delta$ is used for download service calls. The advantages of delivered posting provider demands up_ben, the advantages of served download provider demands $down\_ben$, and the penalties of delivered install service order collective with stale data pen_down should all be added up to form tot_ben, which represents the overall benefits obtained from the served upload and download service requests. Tot ben is thus represented as

$$tot\_ben = up\_ben + down\_ben + pen\_down \quad (9)$$

Initially, up_ben could be written as

$$up\_ben = \epsilon.\delta.cred \quad (10)$$

where $cred_{ul}$ is the amount of credit for every served uploading service order group and represent the number of service order groups in the uploading demand table $down\_tab$. The expression for second $down\_ben$ is

$$down\_ben = \omega.(1-\pi).\pi.cred\_ul \quad (11)$$

wherein ω is the total amount of download service order groups in the $down_req$and $cred\_dl$ is the number of credits for each downloaded download service request group that was successfully completed. A second expression of pen_dl is

$$pen_{dl} = \omega.(1-\pi).(1-\pi) - kl \quad (12)$$

Considering size of data, grouping demand deadlines, and information acceptance everyone has multiple evaluation schemes and types, the purpose of this procedure is to minimize any adverse effects from various metrologies. The AZ then determines the jth schedule parameter's probability using the given equations:

$$Entropy_j = \frac{1}{\ln N}\sum_{i=1}^{N}\left(G_{ij}^{ent}.lnG_{ij}^{ent}\right), j \in [1,3] \quad (13)$$

Where in G_{ij}^{ent} is the jth schedule variable linked to the service order category d_i, and therefore is denoted as

$$G_{ij}^{ent} = \frac{x_{ij}}{\sum_{k=1}^{N} x_{kj}} \quad (14)$$

The entropy value of the jth schedule parameter μj could be described as follows based on the theory notion of multiple criteria strategic planning and entropy:

$$\mu j = \frac{1-entropy\ (j)}{\sum_{k=1}^{3}(1-entropy\ (k)}, j \in [1,3] \quad (15)$$

Last but not least, it is possible to determine the delivering precedence of the service order grouping di, represented by $prio(i)$, using

$$prio(i) = 1 - \frac{\sum_{j=1}^{3}(\mu j.X_{ij})}{\sum_{k=1}^{N}\sum_{j=1}^{3}(\mu j.X_{kj})}, i \in [1,N] \quad (16)$$

The piece of data would be upgraded first when the uploading service requests are handled sooner, allowing the download service requests to acquire the most recent versions of the data items. Additionally, the very same service scheduling model is applied to service calls for both downloading and uploading. Because a separate service demand table is used for uploading and downloading customer inquiries, correspondingly, this system is created with the considerations of scalability and versatility for prospective growth and enhancement in the long term.
Step-1 analyse the network factors
Step-2 initiate route finding
Step-3 obtain two hop discovery
Step-4 initiate priority scheduling service
Step-5 find $down\_ben$ and pen_down to obtain tot_ben
Step-6 determine the schedule using entropy

4. Performance analysis

The performance of our proposed reinforcement learning-based topology-aware routing protocol with priority scheduling (RLTARP) is carried out by compared with three existing methods such as DroneCOCoNet [12], Markov decision process (MDP) [15] and deep deterministic policy gradient (DDPG) [16].

4.1 Simulation setup

In a 1000 m × 1000 m × 400 m 3D area where drones are placed for surveillance purposes, nodes are uniformly distributed. Drones can fly at heights ranging from 50m to 200m, although this article will primarily focus on drones that fly at low altitudes. The drones move at speeds ranging from 12 m/s to 30 m/s. The drones' maximum broadcast range is set to 350 meters.

Received: April 18, 2023. Revised: July 14, 2023.

Table 2. Analysis of PDR

No. of nodes	Drone-COCoNet	MDP	DDPG	RLTARP
10	10.2694	12.831	10.23	14.3854
20	28.1188	30.199	25.67	34.2574
30	51.9462	54.901	53.58	56.2568
40	65.2473	71.114	73.98	78.2522
50	79.5436	86.294	86.4	94.9474

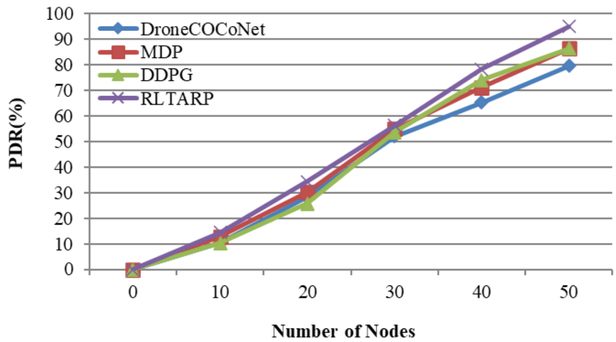

Figure 2. Packet delivery ratio

4.2 Comparative analysis

1- Packet delivery ratio

The PDR is decided by the number of successfully delivered data packets at the destination node and the number of data packets originating from the source node. This metric excludes redundant data packets. PDR reflects the data delivery efficiency of the routing protocol.

Fig. 2 depicts the shows packet delivery ratio comparison of existing DroneCOCoNet, MDP, DDPG and proposed RLTARP. X axis and Y axis shows that number of nodes and the values obtained in percentage respectively. When compared, existing DroneCOCoNet, MDP and DDPG methods achieve 39.18%, 42.55% and 43.2% of Packet delivery ratio while the proposed RLTARP method achieves 46.34% of Packet delivery ratio which is 7.2% better than DroneCOCoNet, 4.21% better than MDP and 3.14% better than DDPG method.

2- Average end to end delay

The average time required for a successful data transmission between the source and destination is defined as the average E2E.

Fig. 3 depicts the shows end to end delay comparison of existing DroneCOCoNet, MDP, DDPG and proposed RLTARP. X axis and Y axis shows that number of nodes and the values obtained in percentage respectively. When compared, existing DroneCOCoNet, MDP and DDPG methods achieve 94.55%, 80.4% and 43.2% of Packet delivery ratio while the proposed RLTARP method achieves

Table 3. Analysis of end to end delay

No. of nodes	Drone-COCoNet	MDP	DDPG	RLTARP
20	52.289	39.592	32.5	29.343
40	85.482	71.912	73.7	15.769
60	12.212	83.281	82.7	12.227
80	37.379	18.934	45.4	11.338
100	79.985	58.912	43.6	16.268

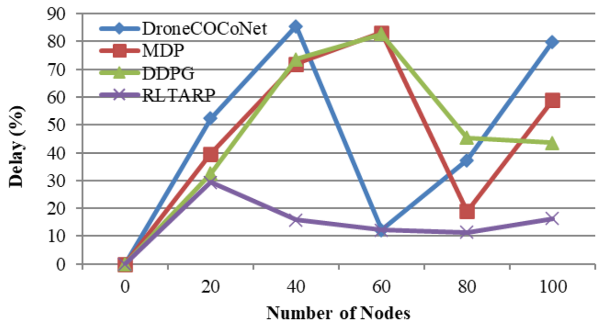

Figure. 3 End to end delay

Table 4. Analysis of routing overhead

No. of nodes	Drone-COCoNet	MDP	DDPG	RLTARP
20	56.7	61.4	72.3	21.5
40	59.4	64.3	73.6	25.6
60	58.4	65.4	76.4	26.44
80	56.2	66	71.4	23.2
100	55.9	66.7	70.9	22.65

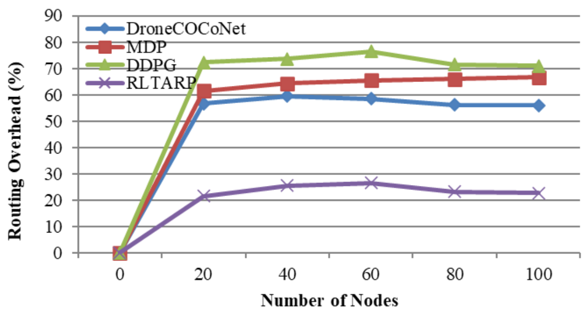

Figure. 4 Comparison of routing overhead

16.45% of packet end to end delay which is 78.1% better than DroneCOCoNet, 63.95% better than MDP and 26.75% better than DDPG method.

3- Routing overhead

The number of control packets transmitted by a routing protocol is defined as the routing overhead. Routing overhead includes the Hello packets and node location information inserted in the packet header for topology construction and routing decisions.

Fig. 4 depicts the shows routing overhead comparison of existing DroneCOCoNet, MDP, DDPG and proposed RLTARP. X axis and Y axis

Table 5. Analysis of energy consumption

No. of nodes	Drone-COCoNet	MDP	DDPG	RLTARP
20	24.6	17.8	23.4	14.2
40	23.1	18.6	21.6	13
60	21.7	19.4	21	12.7
80	22.5	17.6	20.9	13.2
100	21.8	16	20.5	13.9

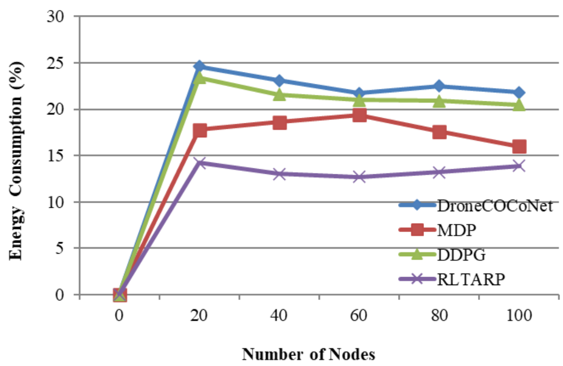

Figure. 5 Comparison of energy consumption

shows that number of nodes and the values obtained in percentage respectively. When compared, existing DroneCOCoNet, MDP and DDPG methods achieve 59%, 69.6% and 76.5% of routing overhead while the proposed RLTARP method achieves 16.45% of routing overhead which is 42.55% better than DroneCOCoNet, 53.15% better than MDP and 60.05% better than DDPG method.

4- Energy consumption:

Energy consumption is defined as the amount of power consumed by each UAV node during the communications. Node energy consumption have major impact on overall network lifetime.

Fig. 5 depicts the shows energy consumption comparison of existing DroneCOCoNet, MDP, DDPG and proposed RLTARP. X axis and Y axis shows that number of nodes and the values obtained in percentage respectively. When compared, existing DroneCOCoNet, MDP and DDPG methods achieve 23%, 19% and 21% of energy consumption while the proposed RLTARP method achieves 13% of energy consumption which is 10% better than DroneCOCoNet, 7% better than MDP and 8% better than DDPG method.

5- Network lifetime:

The network lifetime is expressed as the total routing time until the first node dies. A longer network lifetime indicates more efficient routing.

Fig. 6 depicts the shows network lifetime comparison of existing DroneCO-CoNet, MDP, DDPG and proposed RLTARP. X axis and Y axis shows that number of nodes and the values obtained in percentage respectively. When com-pared, existing DroneCOCoNet, MDP and DDPG methods achieve 67.5%, 76.4% and 87.5% of network lifetime while the proposed RLTARP method achieves 97.6% of network lifetime which is 30.1% better than DroneCOCoNet, 11.2% better than MDP and 10.1% better than DDPG method.

Table 6. Analysis of network lifetime

No. of nodes	DroneCOCoNet	MDP	DDPG	RLTARP
20	64.7	74.3	83.58	97.6
40	66.5	75.7	85.5	95.7
60	62.5	78.9	83	98.6
80	61.8	79	89.3	94.6
100	60.5	76.6	81.6	94

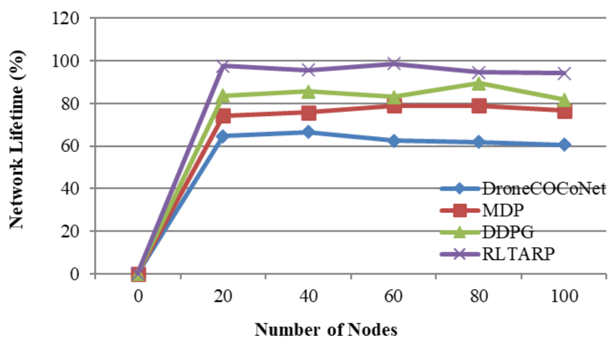

Figure. 6 Comparison of network lifetime

Table 7. overall comparative analysis

Parameters	DroneCOCoNet	MDP	DDPG	RLTARP
Packet delivery ratio (%)	39.18	42.55	43.2	46.34
Average End to end delay (%)	94.55	80.4	43.2	67.49
Routing overhead (%)	59	69.6	76.5	16.45
Energy consumption (%)	23	19	21	13
Network lifetime (%)	67.5	76.4	87.5	97.6

5. Conclusion

Owing to new hardware and software, the use of communications technology in precision farming has grown quickly. Additionally, many advanced methods are indeed being created more and more in various fields to enhance and improve agriculture operations. Particularly remarkable is the apparent advantage of UAV utilization in recent research of precision farming. Additionally, it is a sector that is constantly developing new inventions and is evolving quickly. In order to quickly respond to changes in network topology, this reinforcement learning-based topology-aware routing protocol with priority scheduling (RLTARP) esti-mates the link duration and dynamically modifies the hello interval and link holding time. A routing protocol's performance might be enhanced by multi-path-based load balancing. The proposed RLTARP is compared with three state of art methods and hence it produces 46.34% of packet delivery ratio, 67.49% of end to end delay, 16.45% of routing overhead, 13% of energy consumption and 97.6% of network lifetime. In our upcoming work, we'll take multi-path-based load balancing into account when we create the routing protocol.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

"Conceptualization, methodology, writing—review and editing, supervision, project administration, A.H. Abbas; software, validation, A.H. Najim; formal analysis, investigation, resources, data curation, K. Al-sharhanee; writing—original draft preparation, visualization, funding acquisition, H.M. Hariz.

References

[1] P. Patel, "Agriculture drones are finally cleared for take off [News]", *IEEE Spectrum*, Vol. 53, No. 11, pp. 13 – 14, 2016.

[2] D. Murugan, A. Garg, and D. Singh, "Development of an Adaptive Approach for Precision Agriculture Monitoring with Drone and Satellite Data", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 10, No. 12, 2017.

[3] P. Tripicchio, M. Satler, G. Dabisias, E. Ruffaldi and C. A. Avizzano, "Towards Smart Farming and Sustainable Agriculture with Drones", In: *Proc. of International Conference on Intelligent Environments (IE), Prague, Czech Republic*, pp. 140-143, 2015.

[4] R. F. Maia, I. Netto, and A. L. H. Tran, "Precision agriculture using remote monitoring systems in Brazil", In: *Proc. of IEEE Global Humanitarian Technology Conference (GHTC)*, San Jose, CA, USA, pp.1-6, 2017.

[5] D. Murugan, A. Garg, and D. Singh, "Development of an Adaptive Approach for Precision Agriculture Monitoring with Drone and Satellite Data", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 10, No. 12, pp. 5322–5328, 2017.

[6] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, "A review on UAV-based applications for precision agriculture", *Information*, Vol. 10, No. 11, p. 349, 2019.

[7] H. Jawad, R. Nordin, S. Gharghan, A. Jawad, and M. Ismail, "Energy-efficient wireless sensor networks for precision agriculture: a review", *Sensors*, Vol. 17, No. 8, p. 1781, 2017.

[8] M. Fahad, T. Javid, H. Beenish, A. A. Siddiqui, and G. Ahmed, "Extending ONTAgri with service-oriented architecture towards precision farming application", *Sustainability*, Vol. 13, No. 17, p. 9801, 2021.

[9] Y. Mekonnen, S. Namuduri, L. Burton, A. Sarwat, and S. Bhansali, "Review—machine learning techniques in wireless sensor network-based precision agriculture", *Journal of the Electrochemical Society*, Vol. 167, No. 3, p. 037522, 2019.

[10] K. S. Reddy, Y. M. Roopa, K. R. LN, and N. S. Nandan, "IoT based smart agriculture using machine learning", In: *Proc. of 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, pp. 130-134, 2020.

[11] P. K. Dutta and S. Mitra, "Application of agricultural drones and IoT to understand food supply chain during post COVID-19", *Agricultural Informatics: Automation Using the IoT and Machine Learning*, pp. 67-87, 2021.

[12] Q. Chengyi, P. Calyam, J. Yu, A. Vandanapu, O. Opeoluwa, K. Gao, S. Wang, R. Chastain, and K. Palaniappan. "DroneCOCoNet: Learning-based edge computation offloading and control networking for drone video analytics", *Future Generation Computer Systems*, Vol. 125, pp. 247-262, 2021.

[13] Jang, Younghoon, S. M. Raza, M. Kim, and H. Choo, "Proactive handover decision for UAVs with deep reinforcement learning", *Sensors*, Vol. 22, No. 3, p. 1200, 2022.

[14] Nguyen, K. Khac, A. Masaracchia, V. Sharma, H. V. Poor, and T. Q. Duong. "RIS-assisted UAV communications for IoT with wireless power transfer using deep reinforcement learning", *IEEE Journal of Selected Topics in*

Signal Processing, Vol. 16, No. 5, pp. 1086-1096, 2022.

[15] Khodaparast, S. Saeed, X. Lu, P. Wang, and U. T. Nguyen, "Deep reinforcement learning based energy efficient multi-UAV data collection for IoT networks", *IEEE Open Journal of Vehicular Technology*, Vol. 2, pp. 249-260, 2021.

[16] R. Dhaya, R. Kanthavel, and A. Ahilan, "Developing an energy-efficient ubiquitous agriculture mobile sensor network-based threshold built-in MAC routing protocol (TBMP)", *Soft Computing*, Vol. 25, No. 18, pp. 12333-12342, 2021.

[17] Ananthi, J. Vijitha, and P. S. H. Jose. "Mobility Management UAV-based Grouping routing protocol in flying ad hoc networks for biomedical applications", *International Journal of Communication Systems*, Vol. 36, No. 1, p. e5362, 2023.

[18] Tazibt, C. Yasmine, N. Achir, and T. Djamah, "Online drone-based data gathering strategies for ground sensor networks", *International Journal of Sensor Networks*, Vol. 38, No. 3, pp. 177-190, 2022.

[19] Sarma and H. K. Deva. "Data Aggregation in Internet of Things aiming at Precision Agriculture", In: *Proc. of International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS)*, pp. 271-276, 2021.

[20] A. A. Hourani and K. Gomez, "Modelling cellular-to-UAV path-loss for suburban environments", *IEEE Wireless Communication Letter*, Vol. 7, No. 1, pp. 82–85, 2018.