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REGULAR PAPER

A synthesis of machine learning and internet of things in developing autonomous fleets of heterogeneous unmanned aerial vehicles for enhancing the regenerative farming cycle

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Abstract

The use of Unmanned Aerial Vehicles (UAVs) for agricultural monitoring and management offers additional advantages over traditional methods, ranging from cost reduction to environmental protection, especially when they utilize Machine Learning (ML) methods, and Internet of Things (IoT). This article presents an autonomous fleet of heterogeneous UAVs for use in regenerative farming the result of a synthesis of Deep Reinforcement Learning (DRL), Ant Colony Optimization (ACO) and IoT. The resulting aerial framework uses DRL for fleet autonomy and ACO for fleet synchronization and task scheduling inflight. A 5G Multiple Input Multiple Output-Long Range (MIMO-LoRa) antenna enhances data rate transmission and link reliability. The aerial framework, which has been originally prototyped as a simulation to test the concept, is now developed into a functional proof-of-concept of autonomous fleets of heterogeneous UAVs. For assessing performance, the paper uses Normalized Difference Vegetation Index (NDVI), Mean Squared Error (MSE) and Received Signal Strength Index (RSSI). The 5G MIMO-LoRa antenna produces improved results with four key performance indicators: Reflection Coefficient (S11), Cumulative Distribution Functions (CDF), Power Spectral Density Ratio (Eb/No), and Bit Error Rate (BER).

Keywords Autonomous UAV fleet · IoT · Machine learning · Wireless communications · Regenerative farming

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1 Introduction

Regenerative farming, which is centuries old in some regions of the world, is now regarded as the next evolution in the agricultural sustainability cycle, from restoring soil health, to encouraging plant diversity and biodiversity, to mitigating climate change to producing food sustainably. However, this will require, on the one hand, a change of farmer attitudes and perceptions and, on the other hand, development, and integration of new technologies to farming [1, 2].

Enter the Fourth Industrial Revolution (4IR), a period of rapid technological change that is transforming the way we live, work, and communicate. UAVs and artificial intelligence (AI) are just two of the key technologies driving the 4IR. UAVs can be used for a variety of purposes, including, delivery, surveillance, and mapping whereas AI can be used for the creation of intelligent agents that can reason, learn, and act autonomously. When integrated, they create new and innovative solutions to a wide range of problems, for example, delivering medical supplies to remote regions, monitoring crops for health and disease, and mapping disaster areas. AI is used increasingly to enhance the performance of UAVs, develop new UAV applications, and create innovative interactions with UAVs. The combination of UAVs and AI is having a major impact on the 4IR as their combination enables undertaking of tasks, that were previously not possible, and opening new possibilities for innovation [3, 4].

4IR is now key to the agricultural sector alongside other technologies and applications. Such a smart approach to farming is seeing the use of modern technologies in every stage of the farming cycle to improve harvesting and result in a healthier and sustainable agricultural cycle. Every stage of the farming cycle requires eyes on the ground continuously, and often quick and appropriate action. A bird's eye view from one or more autonomous UAV(s) could provide a welcome relief to a farmer's everyday workload whilst indirectly increasing productivity [5–7].

Figure 1 shows the farming cycle. It consists of 3 main pillars, i.e., logistics, physical, and technological, and 8 stages which are key to sustainable food production.

Figure 2 shows a typical use of UAVs in smart farming which can be in a wide range of roles and agriculture zones such as monitoring crop health and yield, assessing soil quality, and aerial imaging in hard-to-reach zones, and planting seeds, fired into the ground from the air [8, 9]. A growing use of UAVs is in irrigation management, whereby a UAV can assess irrigation levels where this is difficult to assess at ground level because of water pooling or capping, for example. A fleet of UAVs may then be deployed for crop and land irrigation as well as spraying fertilizers and insecticides to nurture crops with nutrients and protect them against disease [10, 11], the latter of which is rarely necessary in regenerative farming.

Farming has always been a dynamic industry, always evolving to meet the demands of a growing global population, and always open to transformative innovations, more recently swarms or fleets of UAVS. The immeasurable benefits to farming of a collective and cohesive intelligence, stretch beyond having multiple UAVs in the sky [12]:

- Precision Farming: using multiple arrays of sensors and cameras and a higher combined payload for data-gathering on crop health, soil conditions, and weather

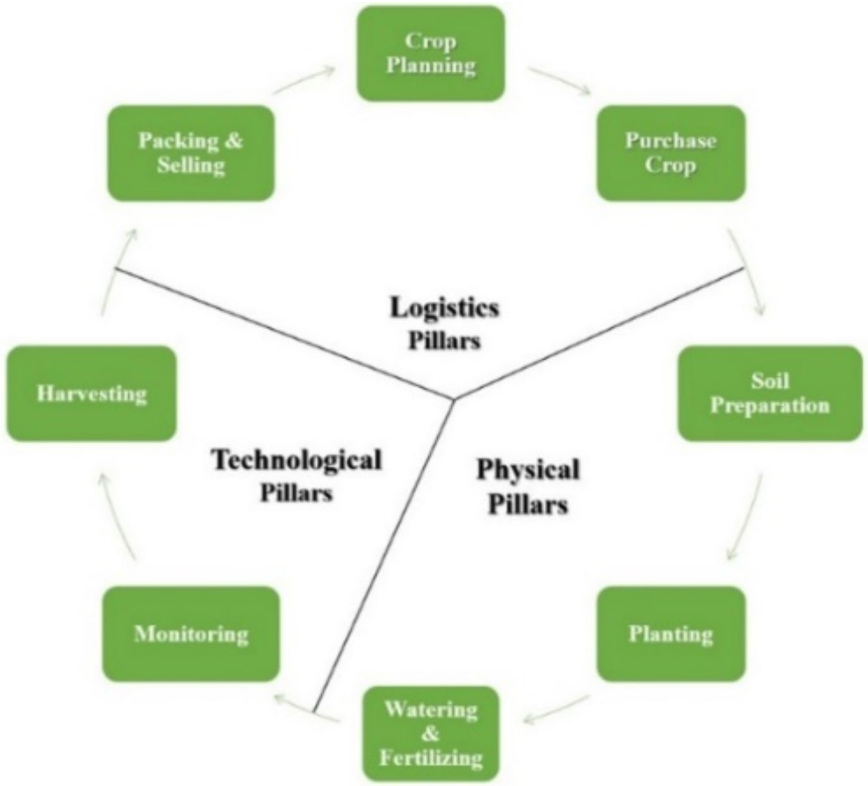

Fig. 1 The farming cycle

patterns, whilst flying in formation over fields. This data allows farmers to make precise decisions about irrigation, fertilization, and pest control, resulting in higher yields and efficient use of resources.

- Efficient Crop Care: programmed to irrigate, apply fertilizers and pesticides with pinpoint accuracy. This reduces overuse and chemical runoff, benefiting both crop quality and the environment. It also eliminates partial compacting or compromising of soil and crop that normally occurs with the use of land machinery like tractors.
- Crop Monitoring 24/7: monitoring crops day and night, delivering insights into changing conditions and potential issues in real-time. Early detection of disease outbreaks or drought stress allows for rapid response.
- Weed Control: identifying, prioritising, and targeting weeds, thus reducing the need for herbicides.

However, despite the long list of benefits, there are also challenges to overcome, including current regulations on airspace navigation, privacy and safety, farmer training, setup and running costs of deployment, data management, the continual problem of battery life, and the lack of GPS which is not uncommon in farmland areas. UAVs fleets are usually set up as homogeneous, i.e. comprising of the same type of UAV,

Fig. 2 UAVs in smart farming

which makes their collective and cohesive behaviour less complex to manage. However, fleet homogeneity can be detrimental with regards to depleting battery life or lack of GPS as, when these challenges arise, the entire fleet will experience these at the same time.

In this paper we present a framework that, firstly, gives autonomy to a fleet of heterogenous UAVs using DRL and, secondly, enables the UAVs to synchronize and schedule tasks using ACO. This fleet of heterogeneous UAVs experiences all the advantages of being a fleet but without the above two shortcomings. We showcase the novelty of our proposal with a proof-of-concept of our autonomous fleet of heterogenous UAVs in arboreal regenerative farming cycles, i.e. seeding, irrigation and harvesting, with minimum amount of intervention.

The novelty of the approach of our framework is our main contribution to research:

- A heterogenous network of UAVs that uses an LEO satellite for UAV management,
- A MIMO-LoRa antenna for ensuring a high data rate and link reliability,
- A separate artificial brain for fleet autonomy using DRL,
- A separate artificial brain for fleet synchronisation and task scheduling using ACO, and.

- A proof-of-concept in a smart regenerative farm.

The rest of this paper is organized as follows: Section II presents a review of related works from which we draw our motivation for synthesising the framework we propose in section III. Section IV details the framework implementation and then discusses the initial results. Section V concludes.

2 Related works review

This section reports on the review of related research works on the use of UAVs in agriculture with a consideration of a healthier life for the planet [13, 14] through a range of responsible planning actions such as charging stations, autonomous navigation, and fleet mission coordination [15]. Some researchers resort to using cooperative game theory to achieve this [16], whilst others to path mapping of ground sensors [17]. Remote sensing and crop monitoring is key in precision smart farming alongside targeted irrigation, fertilisation, and application of pesticides [18–20].

The deployment of fleets of cooperative UAVs for undertaking these tasks on a wider coverage and whilst reducing latency and energy consumption is at the forefront of any attempt to optimise their use [21, 22] with some researchers going as far as employing the use of satellites in the process [23] whilst others stay firmly on the ground with the use of wireless sensor nodes [24, 25]. Whilst their use in precision farming leaves little doubt about their potential benefits, their effectiveness and efficiency as an agricultural tool depend on several factors including route planning, travel time, charging station locations [26, 27], the technology on board that enables the undertaking of scheduled tasks such as land images processing, vegetation index calculation, etc. as well as ground technology [28].

With potentially so many cooperative UAVs up in the sky, one issue that arises, is collision avoidance. Therefore, route planning alone will not be enough to accomplish this. This requires some form of air traffic control not dissimilar to that of aviation, whereby, managing their synchronisation, speed, altitude, and mission time alongside the planning of their route is key to ensuring operational flying success as a fleet [29–33].

Of importance to the smart farmer is pest, insect, and disease management. Therefore, the ability to identify any of these quickly and correctly is crucial in managing the health of a crop and the soil. The literature is not short of proposals for accomplishing this [34–37] with most researchers developing hybrid approaches that use the data collected from ultra-high resolution aerial imaging and soil analysis technology as input in various intelligent models [38–42]. Often a UAV or a fleet form part of an IoT system that includes wireless sensors on, and under, the ground, and therefore their use of the right antenna and transmission module is critical for their ground data collection and transmission process [43–45].

The development of intelligent models takes several forms to enable precision farming, from genetic algorithms [46], to swarm intelligence [47], to deep learning [48, 49], to a fusion such as genetic algorithms and reinforcement learning or multi-agent [50–56]. Irrespective of approach, most researchers seek additionally to achieve energy efficiencies through various means such as commencing data collection and transmission when the signal strength is strong to avoid unnecessary data re-transmission [57].

Table 1 compares the studies above against the proposed model and identifies research gaps that inform our motivation.

3 The proposed approach

Clustering of heterogeneous UAVs raises issues of autonomy and synchronization, therefore, having an intelligent framework as the operational brain is an absolute necessity for their collective and cohesive behaviour. In the section that follows, we describe our proposed framework of two ML Brains, shown on Fig. 3, including mathematical formulations and link budget predictions.

The workflow is a 4-stage process. During stage 1, the framework setups the UAVs to fly autonomously and synchronized and schedules their tasks' priorities. During stage 2, the framework coordinates the leader-follower topology of the fleet in the sky segment with the use of a Micro Air Vehicle Link (MAVLink) with three support functions: *data exchange* with remote real-time transmission, *control* such as taking-off, landing, systematic movement, flight mode variation and safety, and *routing* to the UAV leader 's action plan. A Low Earth Orbit (LEO) satellite coordinates multiple UAV fleets which are equipped with MIMO-LoRa antennas to improve data rate transmission and link reliability [58, 59]. During stage 3, a gateway node receives data from the underground Wireless Sensor Network (WSN) such as soil moisture, temperature, humidity, and water levels, and transmits these to the UAV fleet which the UAVs transmit, in turn, to their leader for transmission to the LEO satellite. During stage 4, the LEO satellite transmits the data to the cloud via a Ground Control Centre (GCC) for storage and data analytics.

The role of the first brain is to enable UAV fleet autonomy using DRL, we call this the DRL brain, and the role of the second brain is to enable UAV synchronization and task scheduling using ACO, we call this the ACO brain [60–64].

Evaluating the probability of reliable command and control between the colonies' leaders and the LEO Satellite is expressed in Eq. (1).

$$\mathrm{P}^{\mathrm{cov}} = \mathrm{P}_{\mathrm{SAT}} + (1 - \mathrm{P}_{\mathrm{SAT}})\ \mathrm{P}^{\mathrm{cov}}_{\mathrm{FAN}} \tag{1}$$

where $\mathrm{P}^{\mathrm{cov}}$ denotes the coverage probability that each colony's leader will receive all messages to control command of their movements as a fleet, $\mathrm{P}_{\mathrm{SAT}}$ denotes the probability that a colony's leader will successfully receive the control command from the LEO satellite, $\mathrm{P}^{\mathrm{cov}}_{\mathrm{FAN}}$ denotes the probability that control commands are successfully received from their neighbours.

In monitoring the network topology, reception connectivity, and coverage, the link budget parameter Received Signal Strength Index (RSSI) is used as a performance indicator. The RSSI is expressed in Eqs. (2) and (3).

Table 1 Related studies versus the proposed model

Ref.	Configuration	AI	Problem Solved	Issues
[21]	Fleet	√	Aerial monitoring, Task assignment	No autonomy
[22]	Fleet	√	Semi-autonomous, Irrigation & pesticides	Semi-autonomous
[23]	Stand-alone	x	Wireless communications, M2M and IoT	Cost, Complexity, No intelligence
[24]	Stand-alone	x	Remote sensing, Assess red pine seedlings	No intelligence, No autonomy, Not with fleets
[25]	Stand-alone	x	Gathering sensed data	No intelligence, No autonomy, Not with fleets
[26]	Stand-alone	√	Path planning, Nodes selection	Semi-autonomous, Not with fleets
[27]	Stand-alone	√	Route planning, Multispectral processing	Not with fleets, Time consuming
[28]	Stand-alone	√	Wireless sensing, Prioritize scheduling	Semi-autonomous, Not with fleets
[29]	Fleet	√	Surveying, Path planning	No task scheduling
[30]	Stand-alone	√	Transmission scheduling	Not with fleets
[31]	Fleet	√	Coverage planning	Semi-autonomous
[32]	Stand-alone	√	Insect monitoring	No task scheduling, Not with fleets
[33]	Stand-alone	√	Insect monitoring	No task scheduling, Not with fleets
[34]	Stand-alone	√	Inspect infected leaves	Not autonomous, Not with fleets
[35]	Stand-alone	√	Spray pesticide, Route navigation	Not with fleets, Fixed navigation
[36]	Fleet	√	Crop monitoring, Path planning	Complexity
[37]	Fleet	√	Route planning, Task allocation	No in-field operations, Semi-autonomous
[38]	Stand-alone	√	Crop counting, Soil health assessment	Semi-autonomous, Not with fleets
[39]	Stand-alone	√	Leaf disease prediction	Not with fleets, Not task scheduling
[40]	Stand-alone	√	Crop monitoring	Not with fleets, No task scheduling
[41]	Stand-alone	√	Crop monitoring, Crop classification	Not with fleets, No task scheduling
[42]	Stand-alone	√	Path plan for pest spray	Not with fleets, No task scheduling
[43]	Stand-alone	x	Soil monitor with sensors	No intelligence, No autonomy, poor signal strength
[44]	Stand-alone	√	Pest detection	Not autonomous, Not with fleets
[45]	Fleet	√	Aerial crop monitoring	No task scheduling, Not with fleets
[46]	Fleet	√	Coverage for precision	No task scheduling
[48]	Stand-alone	x	Aerial crop monitoring	Not autonomous, Not with fleets
[49, 50]	Fleet	√	Coverage for precision	Not autonomous, No task scheduling

Table 1 (continued)

Ref.	Configuration	AI	Problem Solved	Issues
[51, 52]	Fleet	√	Remote sensing, Aerial crop monitoring	No task scheduling, No autonomy
[53]	Stand-alone	√	Path planning	Not autonomous, Not with fleets
[54]	Stand-alone	√	Crop monitoring	Not autonomous, Not with fleets
[55, 56]	Stand-alone	√	Crop monitoring	Not autonomous, Not with fleets
Our	Fleet	√	Synchronization of fleet flying, Task scheduling	

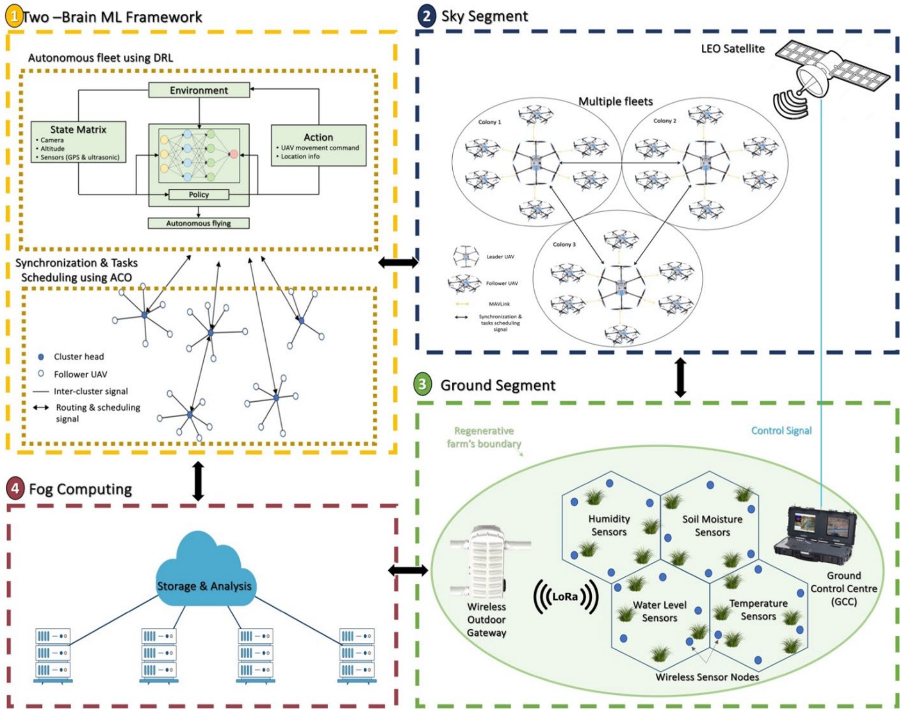

Fig. 3 The framework of ML brains

$$\mathrm{RSSI} = (\mathrm{P_t} + \mathrm{h_t} + \mathrm{h_r} - \mathrm{PL} - \mathrm{L}) \tag{2}$$

$$\mathrm{PL} = 20\log\frac{4\,\pi\ \ (\mathrm{f})\,(\mathrm{d})}{\mathrm{c}} \tag{3}$$

where PL denotes free-space path loss in dB, d denotes distance of transmission (km), f denotes carrier frequency (GHz), c denotes speed of light, $\mathrm{h_t}$ denotes altitude, $\mathrm{P_t}$ denotes transmitter power, $\mathrm{h_r}$ denotes receiver antenna height, and L denotes system losses.

A safe flight without human intervention is the DRL brain's primary mission with a fully autonomous UAV. This will enable the autonomous UAV fleet to manage unexpected and unpredictable emergencies. The DRL brain uses three main parameters: deep agents for learning the best course for rewards, states, and actions, flight path planning for optimising flight paths, and proximity information for avoiding obstacles using proximity sensors and front-facing cameras. The DRL brain is expressed in Eq. (4) to (13).

$$\mathrm{r}(\mathrm{s}, \mathrm{a}) = \mathbb{E}\left[\mathrm{R_t}\,|\mathrm{S_{t-1}} = \mathrm{s}, \mathrm{A_{t-1}} = \mathrm{a}\right] \tag{4}$$

$$\mathrm{G_t} = \mathrm{R_{t+1}} + \mathrm{R_{t+2}} + \mathrm{R_{t+3}} + \ldots + \mathrm{R_T} \tag{5}$$

$$v_{\pi}(s) = \mathbb{E}\left[G_t \,|S_t = s\right] \tag{6}$$

$$v_{\pi}(s) = r\, v_{\pi}(s') \tag{7}$$

$$P(s', r\,|s, a) = P_r\{S_t = s', \quad R_t = r,\ S_{t-1} = s,\ A_{t+1} = a\} \tag{8}$$

$$G_t = E\left[\sum{}_{k=0}^{\infty} y^k R_{t+k+1}\right] \tag{9}$$

$$Q(s, a) = E_{\pi}\left[\sum{}_{k=0}^{\infty} y^k R_{t+k+1}\,|S_t = s,\ A_t = a\right] \tag{10}$$

$$Q_*(s, a) = {}^{\max}_{\pi} Q_*(s, a) \tag{11}$$

$$Q_*(s, a) = E[\,R_{t+1} + y\ {}^{\max}_{a'} Q_*(s',\ a')\tag{12}$$

$$Q_*(s, a) = E[\,R_{t+1} + y\ {}^{\max}_{a'} Q_*(s',\ a') - E_{\pi}\left[\sum{}_{k=0}^{\infty} y^k R_{t+k+1}\right] \tag{13}$$

where $r(s, a)$ denotes expected immediate reward from state s after action a, $\mathbb{E}$ denotes expectation of a random variable, R_t denotes reward at time t, A_t denotes action at time t, S_t denotes stochastic state at time t, and likewise, S_{t-1} and A_{t-1}, G_t denotes return of total reward earned over the course of time, $v_{\pi}(s)$ denotes value of state s under policy π (expected return), r denotes a reward, $v_{\pi}(s')$ denotes value of transition to state s' under policy π, $P(s', r\,|s, a)$ denotes probability of transition to state s' with reward r from state s and action a, k denotes number of actions, $Q(s, a)$ denotes array's Q estimates of taking action a at state s and policy π, $Q_*(s, a)$ denotes array's Q estimates of taking action a at state s under optimal policy.

UAV fleet synchronization and task scheduling is the ACO brain's mission with a fully autonomous UAV. This will enable the fleet to carry out scheduled fleet tasks whilst flying in formation. The ACO brain uses three main parameters: multi-agents, social learning, and dynamic leader selection. As a member of a self-organizing swarm, every UAV learns and adapts to its surroundings and its motion and speed accordingly. A leader and its followers will synchronise first as a colony before they begin carrying out scheduled tasks that are appropriate to their fleet size and always aiming at accelerating convergence and avoiding stagnation. The ACO brain is expressed in equations (14) to (26).

$$p_{ij}^{m}(t) = \frac{\tau_{ij}^{\alpha}\,\beta_{ij}^{\beta}}{\sum_{c\in \mathrm{allowed}_i} \tau_{ij}^{\alpha}\,\beta_{ij}^{\beta}} \tag{14}$$

$$J_{a,k}(t) = \frac{1}{k}\sum{}_{m=1}^{k} J_{a,m}(t) \tag{15}$$

$$\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \sum{}_{m=1}^{k} \Delta\tau_{ij}^{m}(t) \tag{16}$$

$$\tau_{ij}(t) = \begin{cases} \tau_{max};\ \ \tau_{ij}(t) \geq \tau_{max} \\ \tau_{ij}(t)\ \ ;\ \tau_{min} < \tau_{ij}(t) < \tau_{max} \\ \tau_{min}\ ;\ \tau_{ij}(t) \leq \tau_{min} \end{cases} \tag{17}$$

$$\Delta\tau_{ij}^{m}(t) = \begin{cases} \frac{Q}{L_o};\ route\,(i,j)\ \ refers\,to\,optimum\,route \\ \frac{-Q}{L_w}\ ;\ route\,(i,j)\ \ refers\,to\,worst\,route \\ 0\ ;o\ \ \ otherwise \end{cases} \tag{18}$$

$$X_a^{N_c} = X_a^{N_{c-1}} + V_a^{N_c} \tag{19}$$

$$V_a^{N_c} = V_a^{N_{c-1}} \times\ e^{-R.N_c} + rand \times\ c \times\ (X_{mod} - X_a^{N_{c-1}}) \tag{20}$$

$$c = 1 - \log\left(\frac{N_c}{m}\right) \tag{21}$$

$$N_a(t) = \{b\,|d_{ab}(t) < r\} \tag{22}$$

$$x_a(t+1) = x_a(t) + v\cos\theta_a(t) \tag{23}$$

$$y_a(t+1) = y_a(t) + v\sin\theta_a(t) \tag{24}$$

$$v \leq \frac{d\,(1/N)^N}{2\pi} \tag{25}$$

$$d = r - \max_{a,b\in\epsilon_0} d_{ab} \tag{26}$$

where $p_{ij}^{m}(t)$ denotes probability of transition of m^{th} ant at node I on time t, τ_{ij}^{α} denotes pheromone on the edge (i, j), β_{ij}^{β} denotes transit feasibility from node i to node j, $\mathrm{allowed}_i$ denotes set of nodes that are neighbouring i, α and β denote constants influencing, $J_{a,k}(t)$ denotes average path cost, k denotes total ants, ρ denotes rate of pheromone evaporation at every node, cycle, $\Delta\tau_{ij}^{m}(t)$ denotes pheromone rate of the edge, τ_{min} and τ_{max} denote pheromone on each route to a specified minimum and maximum values, L_0 denotes most optimal route length, L_w denotes the current iteration's worst route length, X_i and V_i denote locations and velocities of ants respectively, N_c denotes current number of iterations, c denotes learning behavior factor, X_{mod} denotes demonstrator ant superior to current ant (i.e., a leader), R denotes map and compass factor (between 0 and 1), $N_a(t)$ denotes neighbour of agent a, r denotes circle of radius of colony, $x_a(t)$ and $y_a(t)$ denote coordinates of agent at time t, and $\theta_a(t)$ denotes heading angle of agent a.

For farming, estimation of the Normalized Difference Vegetation Index (NDVI) is carried out by a fleet of autonomous UAVs over different zones capturing a sequence of high-resolution images with which to assess the health of trees and their leaves

[65, 66]. The NDVI verifies and quantifies the existence of live green vegetation with the use of reflected light in the visible and near-infrared bands. Using aerial imagery for NDVI enables a high degree of granularity, efficiency, and pace in assessing plant health during crop monitoring. The NDVI and Mean Squared Error (MSE) are expressed in Eqs. (27) and (28) [61].

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{27}$$

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum \left(\mathrm{y} - \mathrm{y}'\right)^2 \tag{28}$$

where NIR denotes light reflected in the near-infrared spectrum, RED denotes light reflected in the red range of spectrum, n denotes sample size, y denotes actual value, and y' denotes predicted value.

4 Implementation of the proposed approach in regenerative farming

Leveraging of the combined advantage of UAVs, ML and IoT is exploited in the implementation of the proposed framework from training, to testing and validation, the latter of which is showcased in practice for crop monitoring in regenerative farming.

Figure 4 shows a Mission Planner that is used when the UAV fleet is sweeping a farm in a strip pattern search. The yellow lines in Fig. 4 show the search pattern, with the search start and end denoted with numbers 1 and 2 respectively. The trial on the figure has been carried out in July 2023 at Taif city in Saudi Arabia at an altitude of 120 m and with footprint reach of $1.5\mathrm{km}^2$. Monitoring a regenerative farm such as this helps with restoring soil health whilst continuing with food production, relying almost exclusively on rainwater. The leader of each colony establishes direct communication links with its counterparts in other colonies in aid of autonomy, synchronization, and task scheduling. The target of each colony of UAVs is one crop which aims at making efficiencies both in monitoring time and power consumption. A control signal for data transfer is established between the colonies' leaders and the LEO satellite to transmit their data. The time necessary for a complete sweep is relatively the same across all fleets at 14.2 min.

The data from this is used in the training of the fleets of UAVs to fly autonomous and collect NDVI data from the regenerative farm, which feature a visibly livelier greener colour against the dusty sand colour ground. Figure 5 displays a real-time detection of NDVI data, where each color symbolizes the health of the plants. NDVI uses color to indicate vegetation presence and density, with green indicating the presence of a healthy vegetation, yellow to red indicating a lesser presence but of a less healthy vegetation, and brown to black indicating little to no vegetation, e.g., Urban or wasteland. This visual representation provides a quick assessment of the distribution of green vegetation in an area. NDVI uses a range between – 1 and 1, whereby

Fig. 4 Regenerative farm monitoring using a mission planner

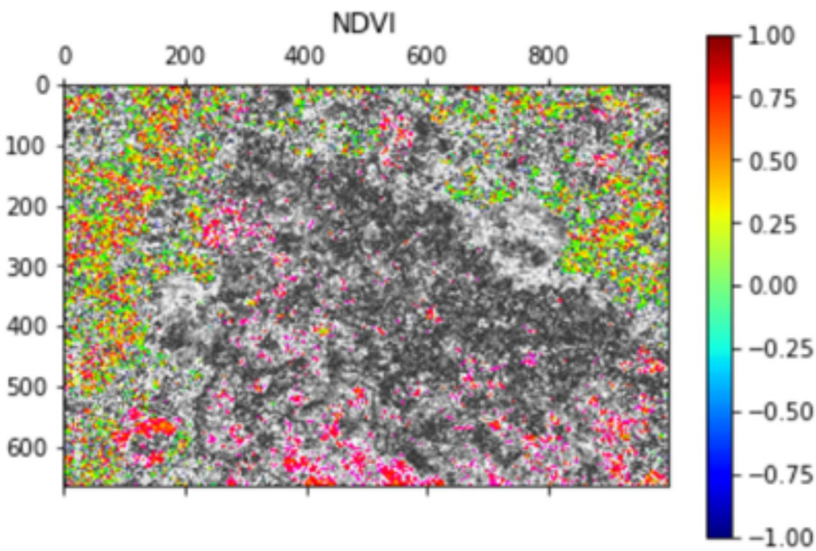

Fig. 5 The NDVI of a regenerative farm

−1 indicates that there are probably no green leaves or dead plants, whilst 1 indicates dense green foliage. The results on Fig. 5 are a reasonable representation of the vegetation in Fig. 4.

The average discounted reward of the DRL brain network, which is adjusted by a process of trial and error is shown in Fig. 6. A significant number of training cycles have been allocated to obstacle avoidance and a high reward point. The mean reward after 34 steps is indicated by the dark colour, while the actual reward value for each repetition is indicated by the light colour. Reward levels drop to zero at the start of each training cycle, which helps UAVs learn safe flying techniques. Crashing is a typical and expected result in the early training cycles. After an initial 578 steps, the flight conduct gets better with time, and reward values gradually go upwards and towards positive rewards. There are also no more crash events.

The ACO brain network's convergence is shown in Fig. 7. The figure shows the average path cost as a function of iterations and reveals a consistent average path cost for the ACO brain network. This highlights the efficacy of the three main components: dynamic leader selection, social learning, and multi-agents.

Figure 8 illustrates the RSSI results of the control signal in relation to the distance between the LEO satellite and the colonies' leaders. This signal is key to transmitting the LEO data to the GCC and in turn to the cloud for storage and further data analytics. RSSI predictions are fundamental since they are used to monitor system performance, network planning, and coverage in achieving perfect reception, which can assess connectivity. The RSSI value floats between −69dBm to -83dBm, which is acceptable for a LoS connectivity. Since the RSSI parameter is linked to path loss, a higher RSSI denotes improved wireless connectivity with the smallest attenuated signal, which in turn will help minimize power consumption.

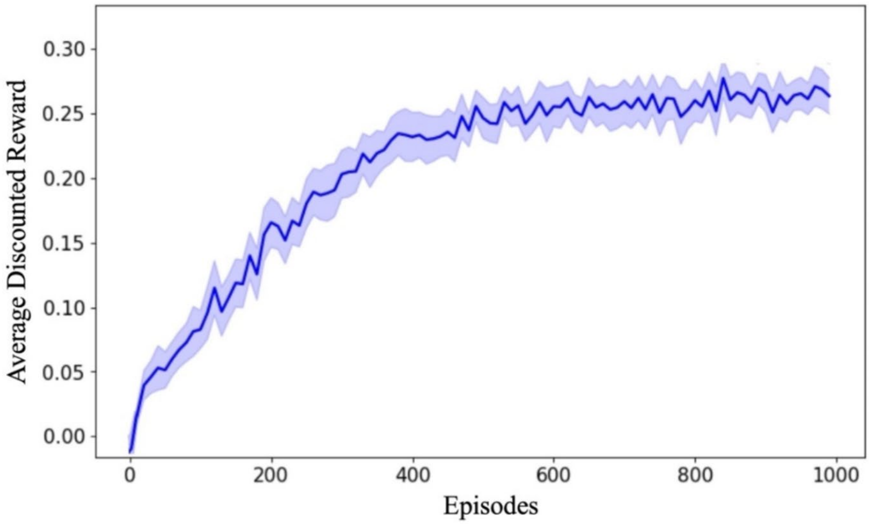

Fig. 6 Average discounted reward of the DRL brain network

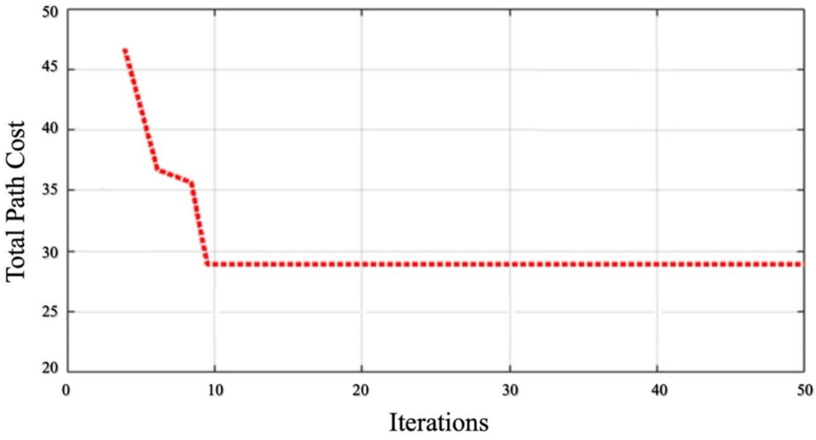

Fig. 7 Average path cost of the ACO brain network

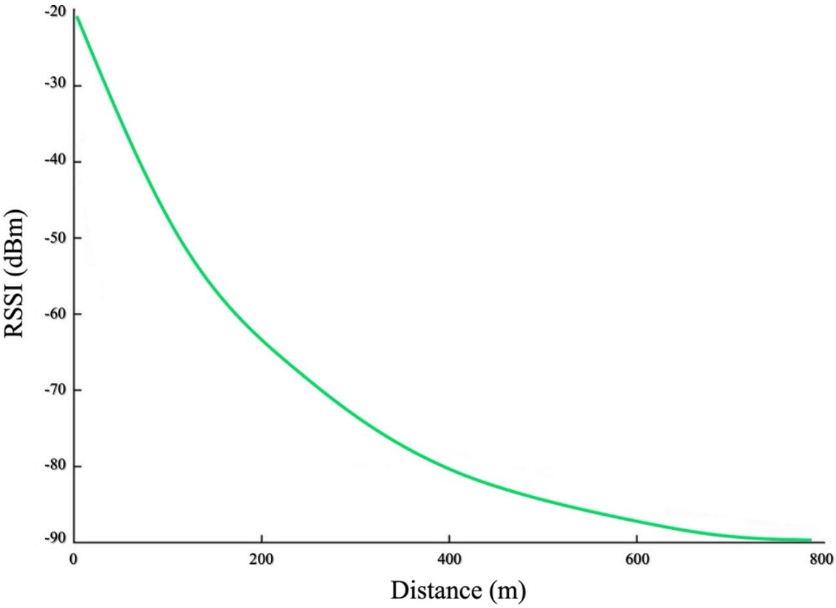

Fig. 8 RSSI results of the control signal

Figure 9 shows the MSE result of the proposed framework which includes three phases: training, testing, and validation. The process validates in 42 iterations, after which error rates do not drop any lower. During the 43rd iteration, training terminates since the error rate starts to increase. The result is fitting because, firstly, the final

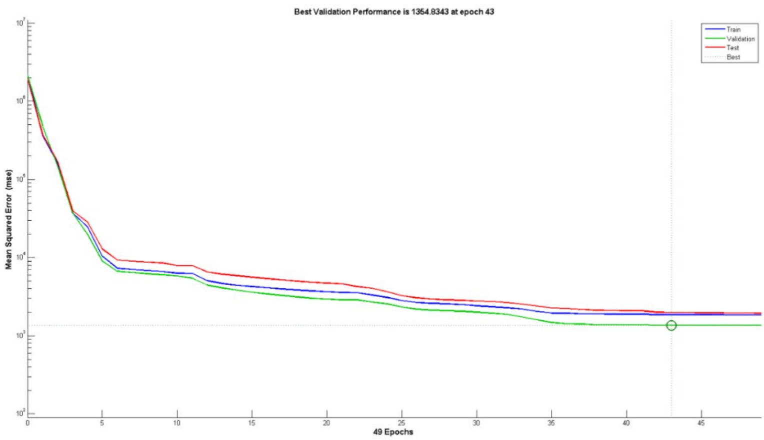

Fig. 9 MSE result of the proposed framework

MSE is small, secondly, the test set error and the validation set error have comparable attributes, and thirdly, no key overfitting happens before iteration 43, when the best validation performance is recorded.

Figure 10 visualizes deployment of both overground and underground sensors in a smart farm, as a proof-of-concept. It shows a bird's-eye view of the conceptual setup that consists of space and ground segments. The space segment shows colonies of UAVs equipped with a variety of devices such as cameras, proximity sensors and 5G MIMO-LoRa antennas that is used in receiving data transmitted from the wireless gateway and then transmitting these to the LEO satellite. The data are destined for the cloud. The ground segment comprises of three parts, namely the GCC for connecting the LEO to the Cloud, the underground and overground sensors for measuring temperature, humidity, rain, and solar radiation, and, a wireless LoRa gateway server for transmitting data from the sensors to the UAVs.

Figure 11 presents the proof-of-concept in six steps. Four types of sensors measure temperature, humidity, soil moisture, and water levels. During the first step, underground and overground sensors sense data. During the second step, the sensed data is transmitted to the wireless gateway server. During the third step, the fleet of UAVs swarm to take images for NDVI analysis and receive data transmitted by the gateway. During the fourth step, the UAVs transmit their data to their UAV leader, with some data redundancy. During the Fifth step, UAV leaders transmit their data to the LEO Satellite which in turn transmits the data to the GCC. During the final step, the GCC transmits the data to the cloud for storage and data analytics in return of actions for precision farming, i.e. managing natural resources, monitoring, and increasing crop productivity, managing harvest, among other.

Figure 12 shows a UAV leader and four terrestrial sensors after their calibration for live data sensing in the proof-of-concept. Figure 13 shows NDVI detection in real-time also in the proof-of-concept. NDVI results are shown as squares with percentages. Values nearing 99% denote healthy plants. We use the Blynk IoT platform

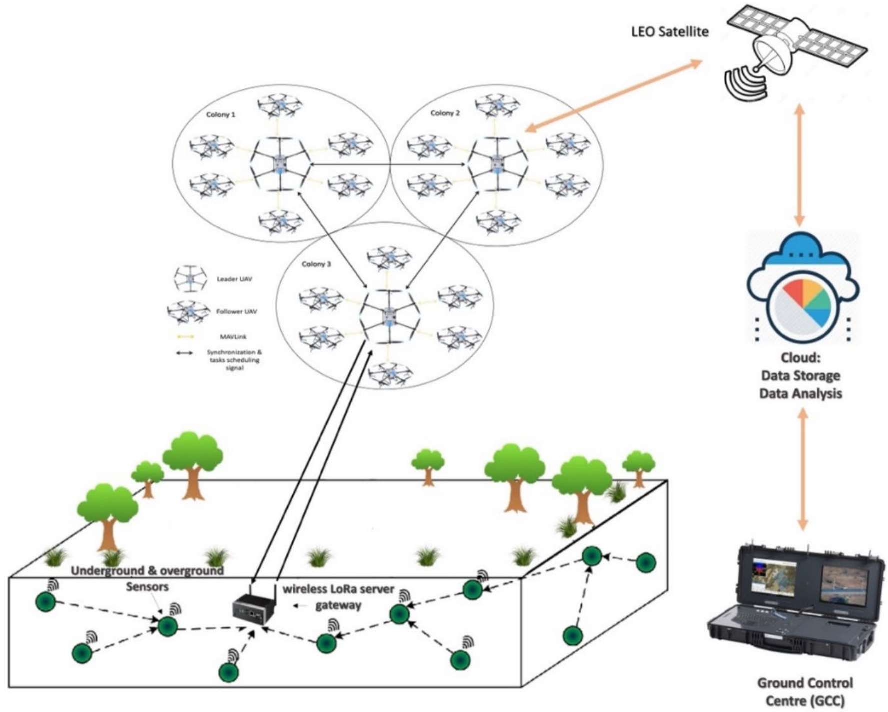

Fig. 10 A bird's-eye view of the proof-of-concept

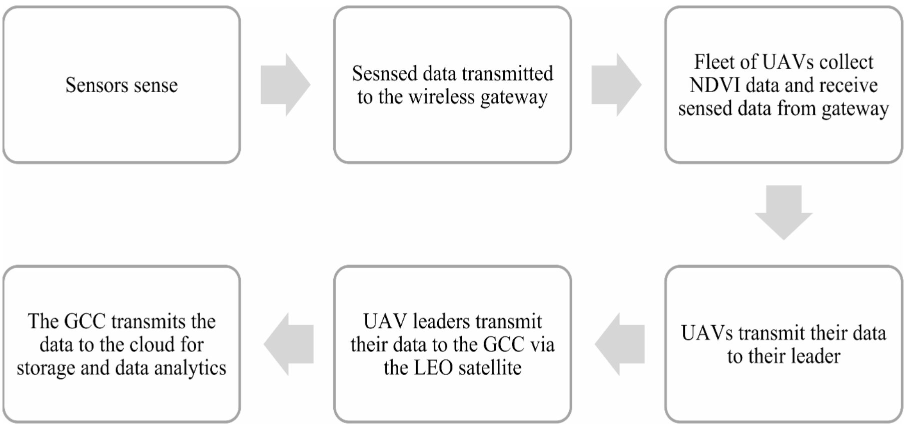

Fig. 11 The proof-of-concept step by step

to record values of all data sensed, and if any of the values recorded are above their threshold will trigger a set of actions that have been derived during data analytics and then stored in the Cloud. One example is water irrigation of the entire field and/or part which in turn will help preserve water resources. Figure 14 is a part of the Blynk

Fig. 12 UAV leader and sensor calibration

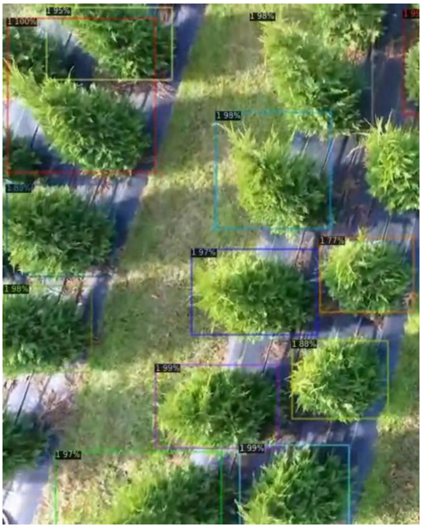

Fig. 13 NDVI detection

IoT dashboard that shows sensed values for temperature, humidity, soil moisture, and water levels.

The link quality between the UAV leader and the wireless gateway relies on several factors, i.e., altitude, operation frequency, transmission power, transmitter and receiver antenna gains, and distance. The use of the 5G MIMO-LoRa antenna yields extended coverage, path loss reduction, improved power consumption with low attenuation loss and high RSSI.

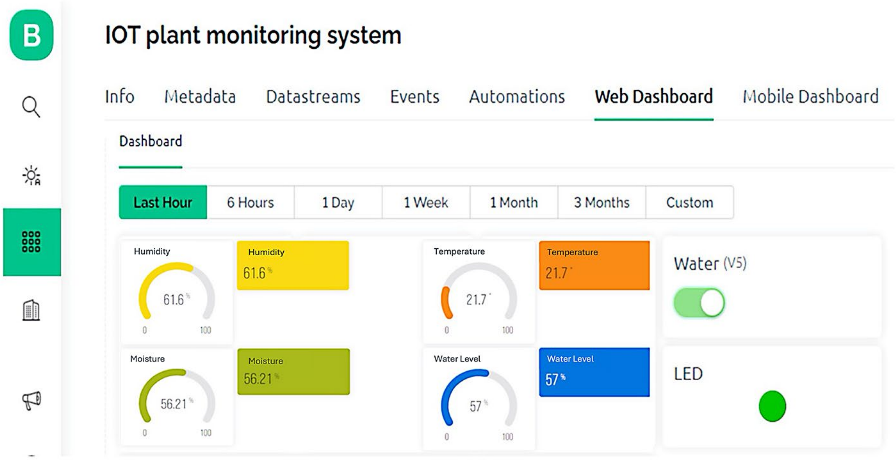

Fig. 14 The Blynk IoT platform used in the proof-of-concept

Fig. 15 S11 results in relation to the 5G MIMO-LoRa antenna

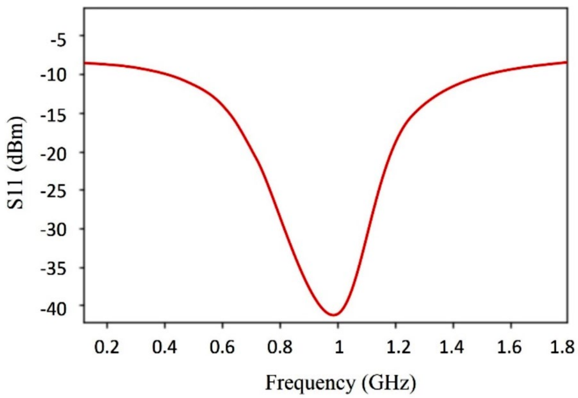

Figure 15 shows the reflection coefficient S11 that calculates the amount of power reflected from the antenna based on its geometry. The S parameter calculates the resonance frequency of the antenna in relation to the resonance of the TM12 and TE modes in order to establish the ratio between reflection and transmission. Figure 16 shows the Cumulative Distribution Functions (CDF) of the Effective Isotropic Radiated Power (EIRP). This plots the cumulative probabilities against power and reveals an array coverage of about 76% with a positive gain at 25dBmW of input power. The maximum allowable path loss enables the maximum cell range to be estimated in relation to the propagation model.

Further validation evaluates the link quality between the UAVs and the wireless gateway using two key QoS performance indicators, namely, the power spectral density ratio (Eb/No), and Bit Error Rate (BER) of a Gaussian distribution channel in relation to altitude, frequency, transmission power, transmitter and receiver antenna gains, bit rate, and distance.

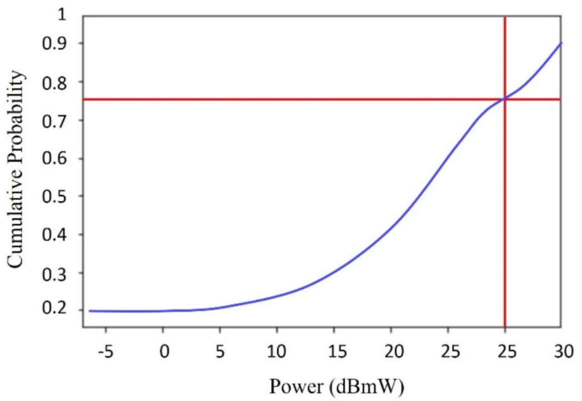

Fig. 16 CDF of EIRP in relation to the 5G MIMO-LoRa antenna

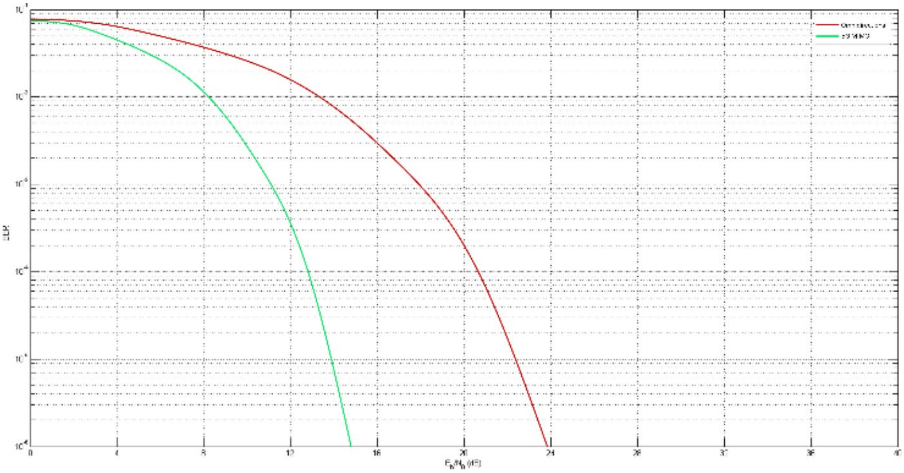

Fig. 17 BER vs. Eb/No of omnidirectional vs. 5G MIMO-LoRa antenna

Figure 17 compares the Eb/No and BER values of an omnidirectional and a 5G MIMO-LoRa antenna. The figure shows the Eb/No performance of the two antennas at their lowest BER of 1×10^{-6}. This suggests the 5G MIMO-LoRa antenna outperforms an omnidirectional antenna. This means that as the Eb/No and BER values decline, the wireless link performance improves. This indicates a channel with low error rates and minimum use of transmission power. This is the result of the diversity gain of the 5G MIMO-LoRa antenna which yields amplification of capacity and link budget, improvement of the coverage range without an increase in the transmission power and with reasonable path loss and fading.

5 Concluding discussion

The integration of AI and Simulation is old wine [67] in new bottles [68] with sustainability now dominating the green agenda. Regenerative farming, as a farming process, dates back centuries, but recently it has firmly established itself into mainstream agriculture as a result of the adoption of sustainable agriculture practices becoming a critical factor for the environment. For a while, agricultural researchers have been synthesising solutions that comprise of UAVs, ML, and IoT for the purpose of optimizing farm operations, from monitoring crop health, to improving crop yields, to establishing a sustainable food supply chain. However, this type of solutions is neither new, and most certainly, nor unique to the farming industry. The entertainment industry, especially the music industry, is one of the pioneers in the adoption of AI [69], ML, UAVs and IoT. In this era of the 4IR and smart things, there is plenty of scope and opportunities for knowledge transfer from such pioneering industries.

Having reviewed what other researchers have already proposed for regenerative farming and what works well in other industries, and motivated by current key challenges, specifically the negative effect of depleting battery life and lack of GPS on a fleet of homogeneous UAVs, we responded first by setting up a fleet of heterogeneous UAVs that can address both challenges. Heterogeneity in the fleet ensures that UAVs will not experience depletion of battery life all at the same time and the inclusion of a LEO satellite in the fleet ensures that UAVs will not experience loss of connectivity [70, 71]. Furthermore, to ensure a high data rate and link reliability, we use a MIMO-LoRa antenna.

We concluded our response by developing an intelligent framework of two artificial brains, one for fleet autonomy using DRL, and one for fleet synchronisation and task scheduling using ACO. We finally showcase the novelty in our development of an autonomous and synchronised fleet of heterogenous UAVs with a proof-of-concept in arboreal regenerative farming cycles, i.e. seeding, irrigation and harvesting, with a minimum amount of human intervention. The performance of our proof-of-concept in regenerative farming is assessed with a set of indicators, i.e. NDVI, MSE RSSI, WSN, and 5G MIMO-LoRa and the data sensed lead to an appropriate set of actions for achieving farming precision.

For future research, we are currently investigating the development of an autonomous fleet of Unmanned Underwater Vehicles (UUVs) to extend our work to cater for shoreline and underwater sea crops such as sea lettuce, sea beans, Irish moss, nori and dulse seaweed, and kelp. Whilst our initial investigation indicates that some of our current aerial infrastructure and framework can be re-purposed for sea crops, working underwater would necessitate revisiting both the communications infrastructure to include UUVs, and the intelligent framework.

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Author contributions The authors have contributed equally to the preparation of the manuscript.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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