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Deployment of an autonomous fleet of UAVs for Assessing the NDVI of Regenerative Farming

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***Abstract*— Unmanned Aerial Vehicles (UAVs) have emerged rabidly as a new technology for crop farming promising to increase the productivity of a farm, on the one hand, and to reduce its farmer's workload, on the other hand, through their integration with other technologies such as Machine Learning (ML), and Internet of Things (IoT). This article aims at developing a framework for deploying an autonomous fleet of UAVs for regenerative farming. Hence, the framework objective is twofold: firstly, is to develop an autonomous fleet of UAVs using Deep Reinforcement Learning (DRL), and, secondly, is to synchronize their flying and schedule their tasks using Ant Colony Optimization (ACO). The implementation of the framework shows great potential when using a set of indicators including, Normalized Difference Vegetation Index (NDVI), Mean Squared Error (MSE) and Received Signal Strength Index (RSSI), to assess its performance for Regenerative Farming.**

Keywords*— *Autonomous UAV Fleet, IoT, Machine Learning, Wireless Communications, Regenerative Farming

I. Introduction

With the standards rising on environmental awareness and education internationally, citizens are becoming increasingly aware of their carbon footprint, especially in relation to the food supply chain. Regenerative farming methodologies are widely regarded as the next evolution in the agricultural sustainability cycle. The term regenerative is frequently used interchangeably with sustainable. It attempts to restore soil health while continuing to produce food. Furthermore, regenerative farming is seen as a set of agricultural practices that help sequester carbon, improve soil quality, retain a large proportion of the rainwater, and reduce erosion and water runoff to provide a more sustainable way of growing food. All, in addition to reducing bare soil, encouraging plant diversity, increasing resilience and biodiversity in the ecosystem. However, adoption of such a model relies on farmer attitudes and perceptions. Moreover, there is a need to develop and integrate several advanced technologies to support such a sustainable regenerative farming model [1].

In relation to the fourth industrial revolution, agriculture takes the centre stage among other technologies and their applications. In many countries, a multitude of innovations compete with one another to yield to a more abundant production, one that will satisfy the growing needs of our generation. A smart approach to farming could see the deployment of modern technologies at every stage of the farming cycle to enhance harvesting and achieve a healthier and more sustainable agricultural cycle. Farming requires eyes firmly on the ground at almost every phase of the farming cycle, and the farmer's experience and swift action is crucial. A bird's eye view from UAV(s) supported with ML to be autonomous could be a superlative alternative in relieving the farmer of some of his mundane workload whilst contributing to increasing a farm's productivity [2-4].

In consideration of their hardware and software capabilities, UAVs can find use in a wide range of roles and heterogeneous agriculture zones. Fig. 1 shows typical UAV uses in smart farming. For example, UAVs may be deployed in crop health and yield monitoring, soil quality assessment, and general aerial view imaging, which for hard-to-reach areas can be both convenient and timesaving [5].

Another example is irrigation management, where a UAV equipped with cutting-edge thermal and conventional cameras may be deployed to detect irrigation issues that are invisible at the ground level, e.g., water pooling or capping. In such cases, UAVs may assume the function of crop and land irrigation. Moreover, UAVs may also assume the functions of spraying fertilizers and insecticides to nurture crops and provide them with much needed nutrients, on the one hand, and protecting the crops against disease, on the other hand. Another UAV usage is planting seeds which can be fired into the ground from high up in the sky [6].

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

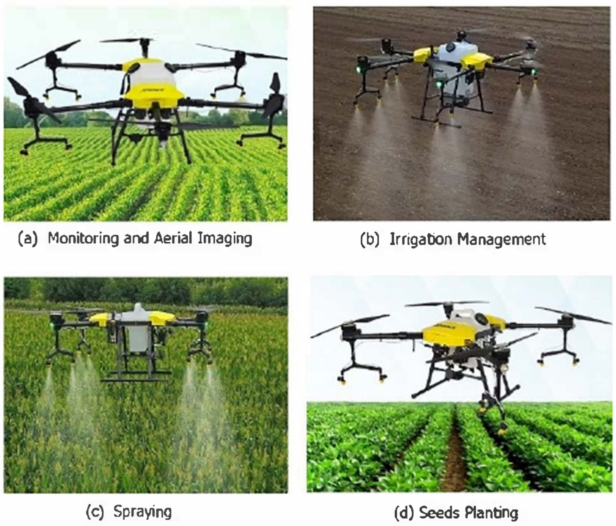

Fig.1: UAVs deployed in smart farming

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II. RELATED WORKS REVIEW

This section reviews related research works on UAVs from an agricultural perspective. To guarantee consistency within the scope, a set of criteria have been used to review related works. The criteria comprise of platform type, network configuration, AI approach, problem solved, and issues. The section concludes with a summary of our own findings, whose purpose is to bring to the fore research gaps and, in turn, to motivate our own work.

The UAV ecosystem can greatly benefit from its simplicity, efficiency, flexibility, rapid deployment, negatable latency, various positioning, line of sight (LOS) connectivity, and wide applicability. Researchers are striving to participate in employing advanced technology that is associated with UAVs to achieve a better life for our planet [7, 8].

Lagkas et al. [9] argue that what is most common with UAVs in precision smart farming is remote sensing, and monitoring to assess and monitor crops. The agricultural industry is very inquisitive when it comes to learning more about the land that they manage and, naturally, have researched aerial systems like UAVs and satellite technology to capture or sense new farmland information, or even efficiently target the application of fertilisers and pesticides [10]. Pinto et al. [11] highlight some missions namely, scouting, monitoring, and inspection, that would greatly benefit from using UAVs.

Fleets of cooperative UAVs are presented in [12] for the purpose of monitoring including agricultural land by using a multi-trip task assignment and optimization approach to serve their objectives. The results ensure that many benefits have been gained including wide coverage, noticeable reductions in latency and energy consumption.

Louta et al. [13] present the use of a fleet of semi-autonomous UAVs to support decision-making for efficiently managing pesticides, irrigation, and task scheduling. A case study presented in [14] uses satellite systems to provide connectivity to smart farms in remote regions of Australia. The space-based system can deliver a seamless Machine-to-Machine (M2M) communication and support IoT applications in farms.

Poudel and Bevilacqua [15] consider a UAV with a point clouds method to assess red pine seedlings. The detection and estimation of the seedlings' height proves promising. However, deep learning and machine learning algorithms are recommended for better results. A UAV is presented in [16] for sensing data in an olive farm via wireless sensor nodes (WSNs) at the ground level. The results indicate that the topology is both reliable and robust.

A path planning for UAVs in open areas like farms is introduced in [17], which aims at reducing travel time using an optimization framework. Their proposed model opts for a charging station across large areas. A route planning in agricultural zones using an automated and optimized UAV is presented [18] to deal with multispectral image processing and vegetation index calculation and visualization.

A study in [19] presents an efficient cluster head selection for WSNs in smart farming. A proposed framework aims at mapping network nodes to increase the wireless sensors' lifespan. The results confirm a good level of sensor energy optimisation via focusing on prioritized scheduling.

Liang and Delahaye [20] present the case for a fleet of UAVs for large scale agriculture and forestry surveying to reduce mission time. Their classification of the optimization parameters either as primary, i.e., path planning, or secondary, i.e., altitude and UAV speed, is key to their process.

Savkin et al. [21] present an autonomous UAV in a 3D trajectory optimization and transmission scheduling on uneven terrains. The work considers collision avoidance with multiple cooperating UAVs. Bromo et al. [22] use reinforcement learning for coverage planning of UAV fleets.

Berger et al. [23] present an integration between an autonomous robot and a UAV for insect monitoring. The authors argue that complexity and time management would increase when utilizing a UAV fleet. Teshome et al. [24] combine UAV imaging and AI for plant phenotyping and immediate resolution of issues identified.

A remote-sensing task is presented in [25] for inspecting possible infected maize leaves using UAV imagery and convolutional neural networks (CNN). The proposed approach shows high efficiency and accuracy in identifying infected maize leaves from an altitude of 5m from the ground. Patrik et al. [26] introduce an autonomous UAV to apply pesticide in farms using a rout navigation algorithm. The navigation uses a fixed starting and landing position for the UAV. This results in a recommendation of a more adaptive navigation to avoid obstacles in real time.

In [27] a fleet of aerial and ground vehicles that optimizes path routing is deployed over agricultural fields for crop management. Whilst the proposed method emphasises the importance of developing multi-agent vehicles for precision farming, it, nevertheless, offers no guarantees on worst- or best-case scenarios.

A particle swarm algorithm for UAVs is used in [28] to optimize route planning and task allocation in agricultural fields and an acceptable energy consumption is achieved. A combined geographic information system with aerial imaging using a UAV is proposed in [29] for rice crop counting and soil health assessment. Counting is carried out in semi-automated mode in case of clusters and the results confirm good accuracy.

TABLE I shows a comparison between related studies against the proposed model. The table has helped identify research gaps from which we draw our own research motivation to inform our proposed model.

TABLE I. RELATED RESEARCH AGAINST THE PROPOSED MODEL

Ref.	Config.	AI	Problem Solved	Issues
[12]	Fleet	√	• Aerial monitoring • Task assignment	• No autonomy
[13]	Fleet	√	• Semi-autonomous • Irrigation & pesticides	• Not fully autonomous
[14]	Stand-alone	x	• Wireless comms. • M2M and IoT	• Cost • Complexity • No intelligence
[15]	Stand-alone	x	• Remote sensing • Assess red pine seedlings	• No intelligence or autonomy • Not with fleets
[16]	Stand-alone	x	• Gathering sensed data	• No intelligence or autonomy • Not with fleets
[17]	Stand-alone	√	• Path plaining • Nodes selection	• Not fully autonomous • Not with fleets

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[18]	Stand-alone	√	• Route plaining • Multispectral image processing	• Not with fleets • Time consuming
[19]	Stand-alone	√	• Wireless sensing • Prioritize scheduling	• Not fully autonomous • Not with fleets
[20]	Fleet	√	• Surveying • Path plaining	• No task scheduling
[21]	Stand-alone	√	• Transmission scheduling	• Not with fleets
[22]	Fleet	√	• Coverage planning	• Not fully autonomous
[23]	Stand-alone	√	• Insect monitoring	• No task scheduling • No with fleets
[24]	Stand-alone	√	• Insect monitoring	• No task scheduling • No with fleets
[25]	Stand-alone	√	• Inspect infected leaves	• Not autonomous • Not with fleets
[26]	Stand-alone	√	• Spray pesticide • Rout navigation	• Not with fleets • Fixed navigation
[27]	Fleet	√	• Crop monitoring • Path plaining	• Complexity
[28]	Fleet	√	• Route planning • Task allocation	• No in-field operations • Not fully autonomous
[29]	Stand-alone	√	• Crop counting • Soil health assessment	• Not fully autonomous • Not with fleets
Proposal	Fleet	√	• Synchronization of fleet flying • Task scheduling	

Our main motivation focuses on fleet autonomy and synchronisation, and once achieved, fleet task scheduling. We aim to demonstrate the novelty of our approach in arboreal regenerative farming cycles, from seed to irrigation to harvesting with minimal intervention.

- Development of an artificial brain for managing fleet autonomy and synchronisation,
- Development of an artificial brain for scheduling fleet tasks over the farmland, and
- Validation of the proposed work with a proof-of-concept scenario in a smart farm.

III. THE PROPOSED FRAMEWORK

In executing complex tasks, cooperative UAVs can deliver greater efficiency and reliability. However, any clustering of UAVs would raise the primary issues of autonomy and synchronization in their functioning. Thus, an intelligent framework is almost necessary in setting up a fleet of UAVs that is functioning efficiently and effectively. This section describes our proposed conceptual framework, shown on Fig.2, which includes its mathematical formulation, the link budget predictions, and the machine learning (ML) framework within.

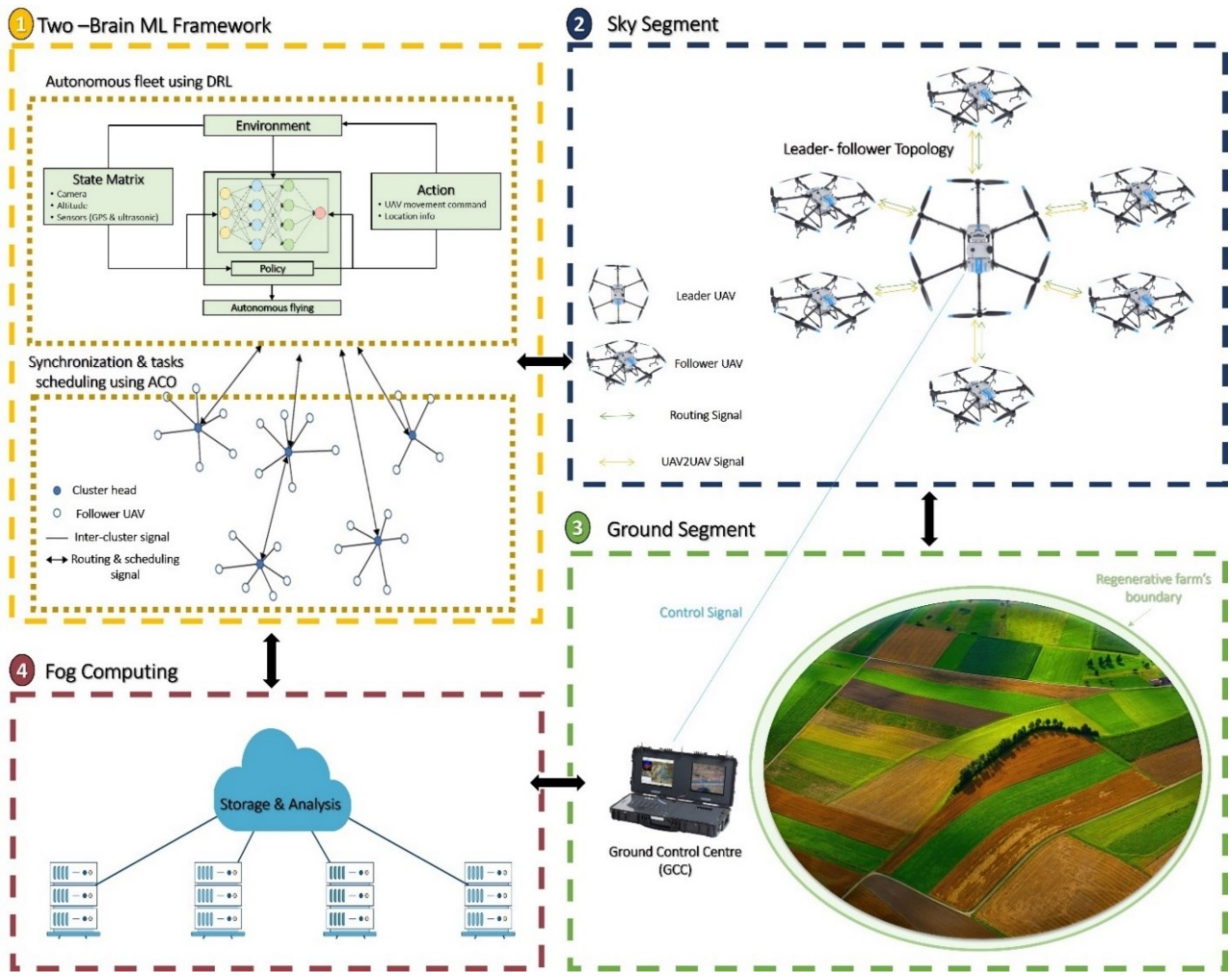

Fig. 2: The proposed conceptual framework

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The framework workflow consists of 4 stages. At stage 1 the ML framework within enables the UAVs to fly autonomously and synchronized and supports prioritised task scheduling. The ML framework within feeds to the sky segment at stage 2, which maintains the leader-follower fleet topology through use of two signals between the UAVs: a routing signal, and a UAV2UAVsignal. The ground segment at stage 3 uses a Ground Control Centre (GCC) to communicate with the UAV leader through a control signal. Data collected by all UAVs are fed to fog computing at stage 4 for analysis and storage.

The Received Signal Strength Index (RSSI) is a vital link budget parameter, which is seen as a performance indicator that helps with monitoring the network topology, reception connectivity, and coverage [30]. RSSI is expressed in equations (1) and (2).

$$\mathrm{RSSI} = (P_t + h_t + h_r - \mathrm{PL} - L) \tag{1}$$

$$\mathrm{PL} = 20 \log \frac{4\,\pi\,(f)(d)}{c} \tag{2}$$

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, h_t denotes altitude, P_t denotes transmitter power, h_r denotes receiver antenna height, and L denotes system losses. The rest of this section details the two-brain ML framework within. One brain uses Deep Reinforcement Learning (DRL) to enable UAV fleet autonomy and the other brain uses Ant Colony Optimization (ACO) to enable UAV synchronization and task scheduling [31-33].

A. *Brain 1: Fleet autonomy with DRL*

This brain's aim is to enable a fully autonomous UAV to have a safe flight without any human intervention using ML. This enables the autonomous UAVs to manage all sorts of unforeseen and unpredictable emergency situations. This work uses the DRL technique to achieve this and this relies on three mains parameters. Firstly, deep agents that will learn the best course for rewards, states, and actions based on previous experience; secondly, flight path planning to set clear goals; thirdly, avoiding obstacles using distance sensors or depth information using front-facing cameras. The DRL for UAV fleet autonomy is expressed in equations (3) to (12).

$$r(s,a) = \mathbb{E}\,[R_t | S_{t-1} = s, A_{t-1} = a] \tag{3}$$

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + \cdots . + R_T \tag{4}$$

$$v_\pi(s) = \mathbb{E}\,[G_t | S_t = s] \tag{5}$$

$$v_\pi(s) = r\, v_\pi(s') \tag{6}$$

$$P(s', r | s, a) = P_r\{S_t = s', R_t = r, S_{t-1} = s, A_{t+1} = a\} \tag{7}$$

$$G_t = E\left[\textstyle\sum_{k=0}^{\infty} y^k R_{t+k+1}\right] \tag{8}$$

$$Q(s,a) = E_\pi\left[\textstyle\sum_{k=0}^{\infty} y^k R_{t+k+1} | S_t = s, A_t = a\right] \tag{9}$$

$$Q_*(a,a) = {}^{\max}{}_{\pi} Q_\pi(s,a) \tag{10}$$

$$Q_*(s,a) = E[\, R_{t+1} + y\ {}^{\max}{}_{a'} Q_*(s', a')] \tag{11}$$

$$E[\, R_{t+1} + y\ {}^{\max}{}_{a'} Q_*(s', a') - E_\pi[\textstyle\sum_{k=0}^{\infty} y^k R_{t+k+1}] \tag{12}$$

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.

B. *Brain 2: Synchronization and task scheduling with ACO*

This brain's aim is to enable synchronization and task scheduling among the UAV fleet using ML. This enables the autonomous UAVs to fly in formation and at the same time carry out scheduled tasks as a fleet. This work uses the ACO technique to achieve this, inspired by three key features: multi-agents, social learning, and dynamic leader selection. Every UAV, by being part of a self-organizing swarm, learns from its surroundings and adjusts its movement and velocity accordingly. A leader and its followers first synchronise as a colony and then begin to carry out scheduled tasks commensurate with their fleet size and always striving to accelerate convergence and avoid stagnation. The ACO for UAV fleet synchronisation and task scheduling is expressed in equations (13) to (25).

$$p_{ij}^m(t) = \frac{\tau_{ij}^\alpha \eta_{ij}^\beta}{\sum_{c \in \mathrm{allowed}_i} \tau_{ij}^\alpha \eta_{ij}^\beta} \tag{13}$$

$$J_{a,k}(t) = \frac{1}{k} \textstyle\sum_{m=1}^{k} J_{a,m}(t) \tag{14}$$

$$\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \textstyle\sum_{m=1}^{k} \Delta\tau_{ij}^m(t) \tag{15}$$

$$\tau_{ij}(t) = \begin{cases} \tau_{max}\ ; & \tau_{ij}(t) \geq \tau_{max} \\ \tau_{ij}(t)\ ; & \tau_{min} < \tau_{ij}(t) < \tau_{max} \\ \tau_{min}\ ; & \tau_{ij}(t) \leq \tau_{min} \end{cases} \tag{16}$$

$$\Delta\tau_{ij}^m(t) = \begin{cases} \frac{Q}{L_o}\ ; & \text{rout(i, j) referes to optimum rout} \\ \frac{-Q}{L_w}\ ; & \text{rout(i, j) referes to worst rout} \\ 0\ ; o & \text{otherwise} \end{cases} \tag{17}$$

$$X_a^{N_c} = X_a^{N_{c-1}} + V_a^{N_c} \tag{18}$$

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

$$c = 1 - \log\left(\frac{N_c}{m}\right) \tag{20}$$

$$N_a(t) = \{b | d_{ab}(t) < r\} \tag{21}$$

$$x_a(t+1) = x_a(t) + v\, \cos\theta_a(t) \tag{22}$$

$$y_a(t+1) = y_a(t) + v\, \sin\theta_a(t) \tag{23}$$

$$v \leq \frac{d\,(1/N)^N}{2\pi} \tag{24}$$

$$d = r - \max_{a,b \in \varepsilon_0} d_{ab} \tag{25}$$

where $p_{ij}^m(t)$ denotes probability of transition of mth ant at node I on time t, τ_{ij}^α denotes pheromone on the edge (i, j), η_{ij}^β denotes transit feasibility from node i to node j, $\mathrm{allowed}_i$ denotes set of nodes that are neighboring 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

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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 neighbor 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.

A core farming process is the calculation of a Normalized Difference Vegetation Index (NDVI) which may be carried out by a fleet of autonomous UAVs synchronizing in flight over different zones and taking a sequence of high-resolution pictures to evaluate the health of trees and leaves [34-36]. The NDVI verifies and quantifies the presence of live green vegetation using a reflected light in the visible and near-infrared bands. The use of aerial imagery for NDVI allows a higher degree of granularity, efficiency, and pace in assessing plant health during a crop inspection. The NDVI and Mean Squared Error (MSE), as performance indicators are expressed in equations (26) and (27).

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \tag{26}$$

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum(\mathrm{y}-\mathrm{y}')^2 \tag{27}$$

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.

IV. FRAMEWORK IMPLEMENTATION

This section presents the predicted results and discusses the main highlights of the proposed solution for regenerative farming. The proposed framework was validated for comprehensive monitoring using the NDVI approach. Fig.3 shows a simulation that uses a set of primary data collected in September 2022 at Al Jouf, Saudi Arabia. Eight regenerative crops are monitored in a circular pattern from an altitude of 500m. These crops vary in size and have a radius of up to 1.5km. Such regenerative farms aim at restoring soil health while continuing with food production and relying almost exclusively on rainwater.

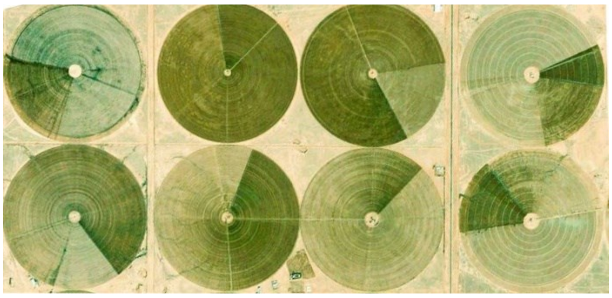

Fig. 3: Crop monitoring in regenerative farms

Fig.4 illustrates the use of a Mission Planner tool to sweep over crops (across yellow lines). These crops exhibit a visibly livelier green colour against the dusty sand colour, which is representative of regenerative farming. The target of each colony of UAVs is one crop which aims at making efficiencies both in monitoring time and power consumption.

Fig. 4: Crop monitoring using a Mission Planner tool

Fig.5 shows three colonies of UAVs on a leader-follow topology. Leaders led and maintained communications for synchronization and task scheduling. The time to complete sweeping is relatively the same across fleets at 19.4 mins. The proposed process starts with calibrating the UAVs' devices. These include electronic speed controllers (ESCs), motors, propellers, flight controller (Pixhawk-4) in case of emergencies, BME280 sensor, battery, and Raspberry Pi 3 microcontroller, and communication module. Then, the leader of each colony establishes a direct communication link with its counterpart in another colony for autonomy, synchronization, and task scheduling using the ML framework. A control signal for data transfer is established between leaders and the GCC. Data gets transferred to fog computing for further analysis and storage.

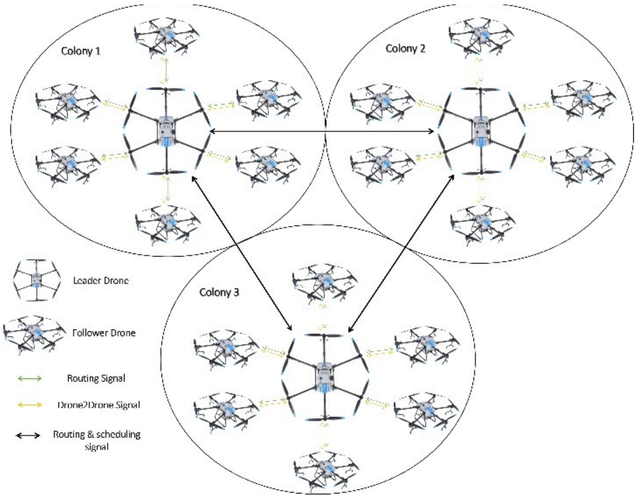

Fig. 5: Leader-follower topology

Fig.6 shows the accumulated reward of the DRL network, which is tuned via a trial-and-error procedure. A considerable amount of UAV training cycles has been done on obstacle avoidance and on reaching the designated goal efficiently and with a high reward point. Light colour refers to the actual reward value for each iteration, whilst dark colour refers to the mean reward after 50 steps. At the beginning of each training cycle during which UAVs establish a correct flying behaviour, rewards fall below zero. This may include crashes, which is an expected normal outcome during early training cycles. Flight behaviour improves over time and reward values steadily increase towards positive rewards with no further crash episodes

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after the first 1670 steps. Training iterations come to an end when UAVs either meet their training goals, or the level of their rewards becomes steady, or the number of iterations reach the pre-set limit.

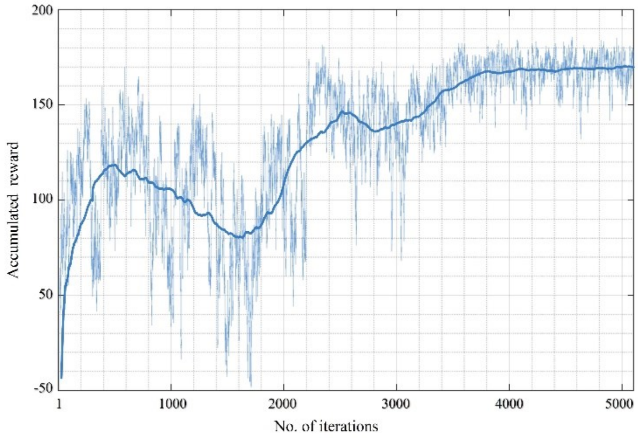

Fig. 6: Accumulated reward of the DRL network

Fig.7 shows the convergence of the ACO network. This presents the average path cost in relation to the number of iterations and reveals a stable average path cost for the ACO network, which in turn reflects on the effectiveness of the technique and its three key features of multi-agents, social learning, and dynamic leader selection.

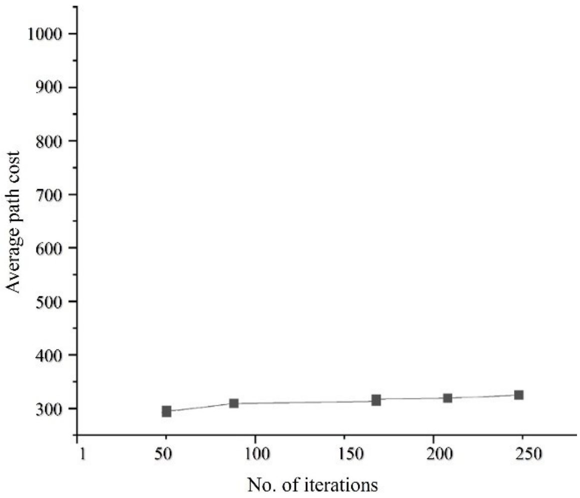

Fig.7: Average path cost of the ACO network

Fig.8 shows the NDVI performance using the RED and NIR bands of the 8 evaluated crops. Fig.9 displays the NDVI numerical performance of these crops. The NDVI values combine the information in the red and NIR bands into a single and representative value by subtracting the reflectance in the RED spectral band from that in the NIR and then dividing this by the sum of the NIR and red reflectance. Healthy vegetation absorbs more red and blue light and seems green to our sight. NDVI ranges between -1 and 1, where -1 denotes that there are probably no green leaves present or dead plants, whilst 1 denotes dense green foliage. NDVI values ranging between -1 and 0 denote dead plants or inanimate objects with no green leaves, values ranging between 0 and 0.33 denoted unhealthy plants, values ranging between 0.33 and 0.66 denote moderately healthy plants, and values ranging between 0.66 and 1 denote very healthy plants.

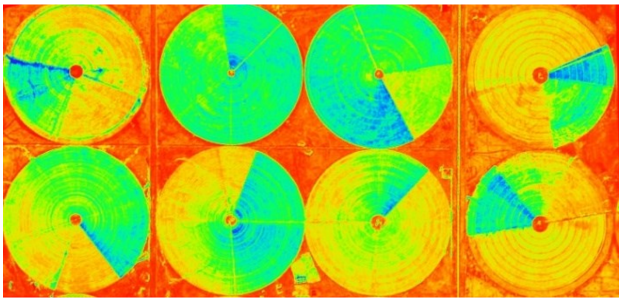

Fig. 8: NDVI results using the RED and NIR bands

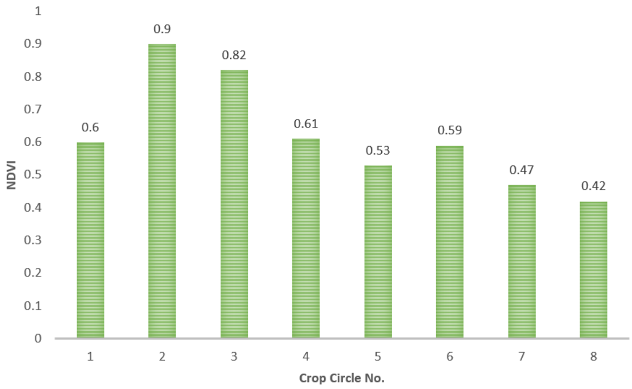

Fig. 9: NDVI numerical results

Fig.10 illustrates the predicted RSSI results in relation to distance. RSSI predictions is vital since it monitors system performance, network planning, and coverage in achieving perfect reception and in our case, evaluating the connectivity between the leader UAVs and GCC. The predicted RSSI value is less than -73dBm, which is acceptable for LoS connectivity. Moreover, the RSSI is linked to path loss, so a higher RSSI denotes improved wireless connectivity with the smallest attenuated signal. This helps with delivering collected data from the leader UAVs to the cloud for analysis and storage in an efficient and timely manner.

Fig.11 shows the MSE performance of the proposed framework. The process verifies in 12 iterations, after which error rates do not fall any lower. During the 13th iteration, training stops as the error rate starts to increase. The result is fitting because, firstly, the final MSE is small, secondly, the test set error and the validation set error have comparable attributes, and thirdly, no key overfitting happens before iteration 13, when the best validation performance is recorded.

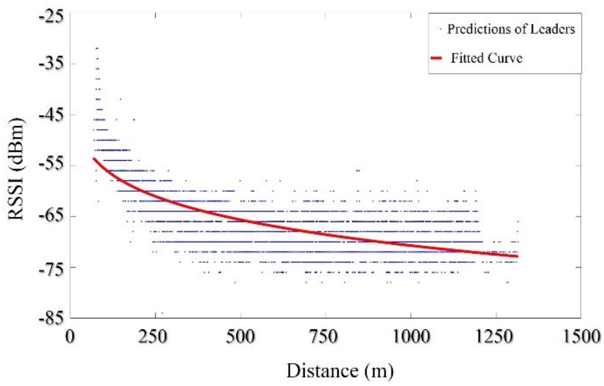

Fig. 10: RSSI predictions of leader UAVs

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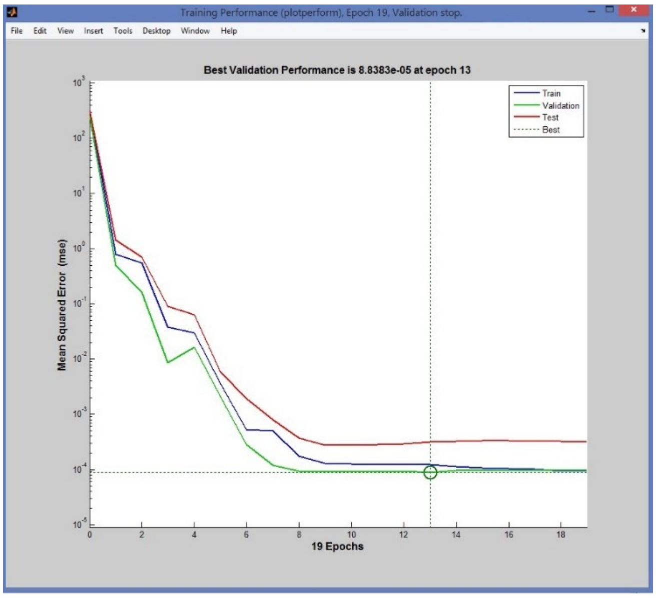

Fig. 11: MSE of the proposed work

V. CONCLUDING DISCUSSION AND FUTURE WORK

Regenerative farming has been around since the dawn of civilization, but it is only recently that it has started moving into mainstream agriculture when healing and restoring soil health and fertility has risen in priority. Agricultural engineers and researchers are striving to use advanced technologies such as UAVs, ML, and IoT to help optimize farms operations, monitor crop growth, improve crop production, and establish a sustainable food supply chain.

Smart farming could prove to be the ultimate solution to food security and environmental challenges. This article presents a framework whose focus is twofold: an autonomous fleet of UAVs synchronised for task scheduling using DRL and ACO. The implementation of the framework reveals promising predictions when evaluating using performance indicators such as NDVI, MSE and RSSI. The parameters adopted are widely considered, and used, as the baseline for carrying out evaluation of frameworks such as the one proposed in this paper.

Naturally, the framework and its implementation may be extended to include a Wireless Sensor Network (WSN) that will support an IoT topology on the ground with live aerial imaging in the sky [37-40] for the holistic management of a smart farm. Such a holistic management approach to smart farming adopts systems thinking to managing resources and provides a support framework for adapting to, and balancing, the four basic ecosystem processes whose successful management is crucial for sustaining a heathy farm: the water cycle, the mineral cycle which naturally includes the carbon cycle, the energy flow, and the community dynamics, i.e., the relationship between all organisms that are integral for the health of any farm ecosystem.

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