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# Integrating machine learning with a positioning mechanism for managing interference and power consumption in a multilayer fleet of unmanned aerial platforms

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**Abstract**
The soaring global demand for ubiquitous wireless connectivity, which epitomizes the digital era, can only be fulfilled with heterogenous networks that, increasingly, need to include aerial platform fleets for a more holistic approach. However, deploying aerial platforms to serve as a fleet would inevitably result in interference, especially for high frequency bands and increased power consumption. This work presents a framework that integrates Machine Learning with a fleet positioning mechanism to mitigate interference and reduce power consumption in a multilayer fleet of aerial platforms. In turn, this optimizes flight time in the short run and the sustainability of the holistic connectivity approach in the long run. Assessment of the post-optimisation Received Signal Strength Index reveals a 16% improvement to pre-optimisation. The work is validated with a proof-of-concept for smart agriculture.

**Keywords** Unmanned aerial platforms · Machine learning · Interference mitigation · Power consumption management

## 1 Introduction

Unmanned aerial High/Low Altitude Platforms (HAP/LAP) are serving an increasingly key role in the development of smart cities. These platforms because of their unique aerial perspective, can be deployed for data collection, infrastructure monitoring, environmental surveillance, last-mile connectivity, and essential services delivery. The presence of aerial platforms in the sky has long been seen as a key advantage, as it capitalises on the strengths of terrestrial and satellite communication systems, whilst avoiding some of their limitations. Figure 1 shows an overview of a multilayer fleet of aerial platforms that support smart applications. Each layer of aerial platforms may include either HAPs, or LAPs, or Tethered Balloons, depending on the layer altitude, and these operate collectively to provide connectivity for various smart applications, e.g., smart buildings, agriculture, energy, healthcare, transportation, and logistics to name a few [1–4].

In comparison to satellite communications, some of the advantages are proximity, Line of Sight (LoS) signal quality, wider coverage footprint, and less attenuation. The International Telecommunications Union (ITU) has assigned high frequency bands for aerial platforms to provide comparable services to satellites with high-speed data rates and large capacity. In contrast to satellites, aerial platforms are environmentally friendly due to their use of renewable energy sources such as sun light and wind. Furthermore, their rapid installation and deployment assumes a much lower expenditure because of their minimal ground-based infrastructure and lower launch costs. The use of aerial platforms has been proven to be a viable alternative infrastructure for remote regions with low user density, setting up Ad Hoc networks for providing disaster relief, and service provision for short-term large-scale events. These strengths characterise the flexibility and re-configurability of aerial platforms [5–7].

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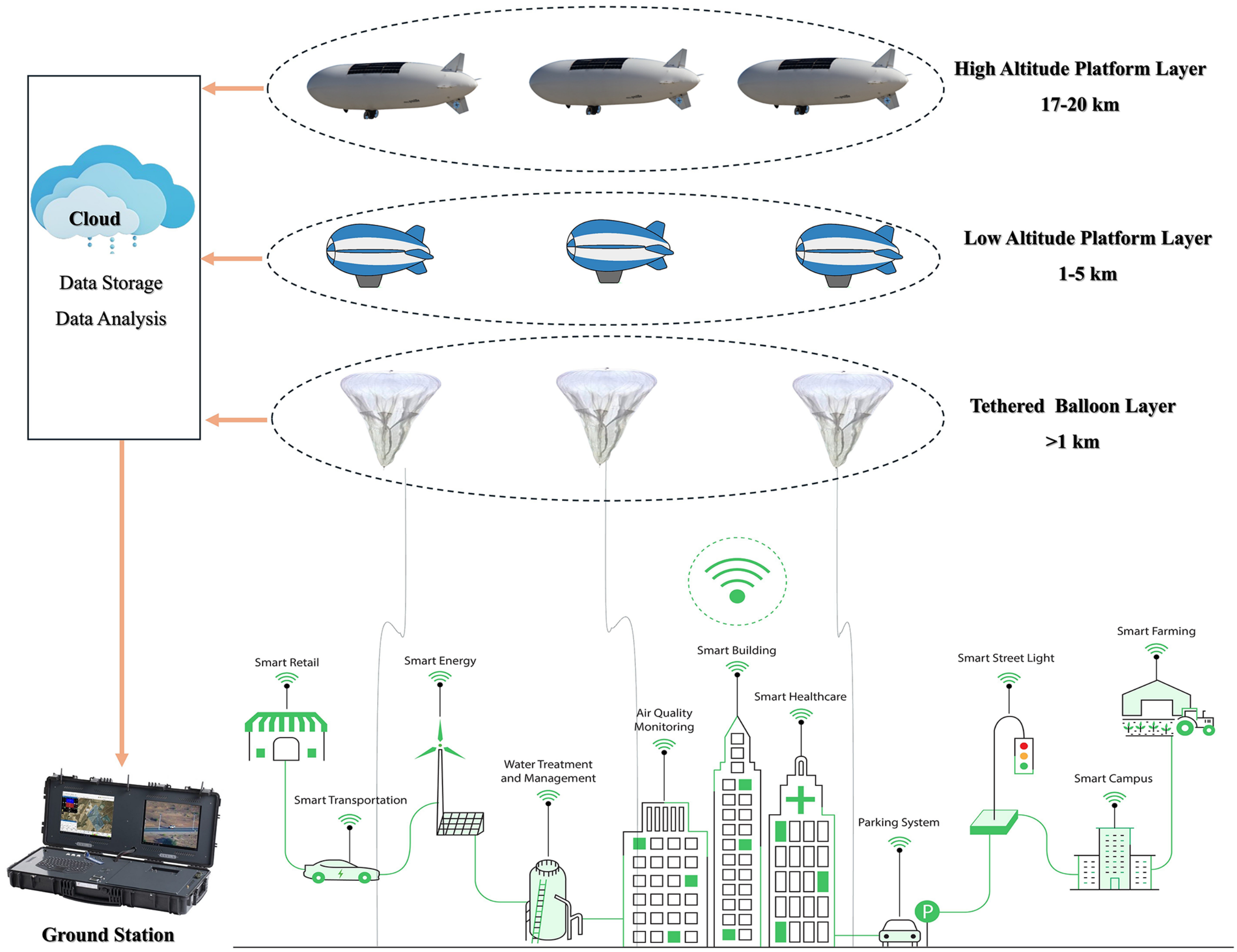



**Fig. 1** A multilayer fleet of aerial platforms for supporting smart applications

The Fourth Industrial Revolution (4IR) has been transforming many industries, and the aerial platform industry has been no exception. Aerial platforms, such as HAPs/LAPs, are fast becoming mature enough to assimilate the pillars of 4IR technologies, e.g., Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT). The assimilation of 4IR technologies in aerial platforms has the potential to bring about significant sustainable gains, not least economic ones that will in turn create a breed of smart applications. The combination of ML and aerial platforms promises to open new directions such as assistive automation, optimization, and autonomy. Overall, navigating the challenges of integrating 4IR technologies with aerial platforms requires a multi-pronged approach involving technological advancements, robust regulations, ethical considerations, and societal engagement to ensure all benefits are harnessed responsibly and equitably [8, 9].

The rest of this paper is organized as follows: Sect. 2 presents a review of related works from which we draw our motivation for the framework we propose in Sect. 3. Section 4 details the framework implementation including a discussion of the initial results. Section 5 concludes.

## 2 Related work review

A review of related works on interference mitigation and power consumption optimisation for aerial platforms reveals numerous proposed solutions for achieving fleet synchronisation and positioning and last-mile connectivity.

Some authors apply various machine learning and optimisation techniques such as Mean-Field Q Learning (MFQL), Reinforcement Learning (RL), Sequential Quadratic Programming (SQP), Mixed Integer Linear Programming (MILP), Geometric Programming (GP) and Pareto to optimise the synchronisation and positioning of their aerial fleet topologies and various Signal to Interference Noise Ratio (SINR) techniques such as S-procedure and Successive Convex Approximation

(SCA) to mitigate interference, whilst ensuring channel reliability between a ground station and aerial platforms to reduce power consumption [10–17]. Their results suggest sufficient but not an optimal balance between interference mitigation and power consumption reduction.

Some authors apply various evolutionary techniques such as swarming, Genetic Algorithms (GA), Serious Gaming, K-means and Deep Reinforcement Learning (DRL) to optimise coverage with their aerial fleet topologies and various antenna configurations to mitigate interference and ensure channel reliability with guaranteed QoS [18–26]. Their results also suggest sufficient balance between interference mitigation and power consumption reduction, but they also reveal that aerial platform scalability has a negative effect on that balance.

Some authors apply a traditional resource allocation approach alongside power management to mitigate interference and reduce power consumption [27]. Their results also suggest sufficient but not optimal balance between interference mitigation and power consumption reduction.

Our comparative review of the above studies reveals challenging research questions. Fleet topologies frequently produce interference and last mile connectivity occasionally assumes increased levels of power consumption. Is there an acceptable tradeoff between aerial platform positioning and synchronization optimality and interference mitigation? Can the tradeoff be extended between channel reliability and power consumption reduction? These research questions have informed our research motivation of mitigating interference alongside reducing power consumption in a multilayer fleet of aerial platforms. To manage these, we have developed a framework that integrates ML with a positioning mechanism for fleet synchronisation that helps to achieve our objectives. We validate our framework in a proof-of-concept application for smart agriculture.

## 3 The proposed framework

Clustering of aerial platforms into a fleet, especially in a multilayer formation, raises issues with aerial positioning and synchronization in mitigating interference and reducing power consumption, in the first place, before even considering the functional objective of such a fleet, i.e. realizing the setup of a heterogeneous network. Therefore, having an intelligent framework as the operational brain of the fleet is an absolute necessity for its efficient and effective functioning in the network. This section describes our proposed framework including its mathematical formulation.

Figure 2 shows the three-phase flowchart of the proposed framework that integrates machine learning with a positioning mechanism for managing interference and power consumption in a multilayer fleet of aerial platforms. During the first phase, the flight parameters of the multilayer fleet of aerial platforms are set up for the different layers, i.e. altitude, elevation angle, flight mode (autonomous or flight path), individual platform position within the fleet, and unique identification via a GPS sensor. During the second phase, a feedback loop is set up with all aerial platforms that are now deployed at different altitudes within the fleet to monitor continuously their connectivity through parameters such as their PL, RSSI, D, and SINR with stationary and mobile ground nodes. During the third phase, data collected during the previous phases are fed to the input layer of a Self-Organizing Map (SOM). The output layer, or map, will either report no changes, which will result in a return to the first phase to attempt securing an acceptable threshold for interference, or increased interference and power consumption beyond the threshold, which will need to be mitigated.

Figure 3 illustrates the positioning mechanism of the proposed framework, including possible interference sources in a multilayer fleet of aerial platforms stationed at different altitudes. The fleet is connected to various receivers including a ground station and fixed and mobile nodes, to the former via a backhaul link for command-and-control functions and to the latter two via wireless links. In such a diverse interference environment, various parameters need to be considered including elevation angle (θ), and azimuth (ϕ), both of which are vital when calculating the separation distance of signal paths between aerial platforms and ground receivers [28–30]. Considering the Earth's surface and curvature when evaluating interference between aerial platforms at various aerial platform altitudes and terrestrial nodes is a noticeable shift from mainstream approaches.

The framework evaluates the interference values of each route, with multipath dominating, considering the prevalence of multipath fading from such a multilayer fleet of aerial platforms. Therefore, it is essential that the aggregate interference is determined by summing up the contributions of all aerial platforms at different altitudes using θ, and ϕ. Calculating interference needs to consider the platform positioning using a suitable modified free space propagation model that includes LoS and beyond LoS. The proposed framework is expressed in Eq. (1) through to (4).

$$\mathrm{I_{route=}}\ 100\frac{\sum_{k=1}^{n}(\mathrm{I_k})}{\mathrm{n}\times\mathrm{N_T}} \tag{1}$$

$$\mathrm{I_{D=}}\ \mathrm{F}(\theta)+\mathrm{G}(\phi)+10\log\left(\frac{\lambda^2}{4\pi}\right)-\mathrm{L_{fr}} \tag{2}$$

$$\mathrm{I_{G=}}\ \mathrm{P_{HG}}-\mathrm{PL}+10\log\left[\Sigma_i\Sigma_j\left(\sqrt{\mathrm{x_{ij(r,d)}}^2+\mathrm{y_{ij(r,d)}}^2}\right)^{-2}10^{\frac{\mathrm{G}(\theta_{\mathrm{P-R}})}{10}}\,10^{\frac{\mathrm{G}(\theta_{\mathrm{R-P}})}{10}}\right]-\mathrm{L_{fr}} \tag{3}$$

$$\mathrm{I_{T=}}\ \mathrm{I_G}-\{10\log\mathrm{K\,T\,B}\}+\mathrm{NF} \tag{4}$$

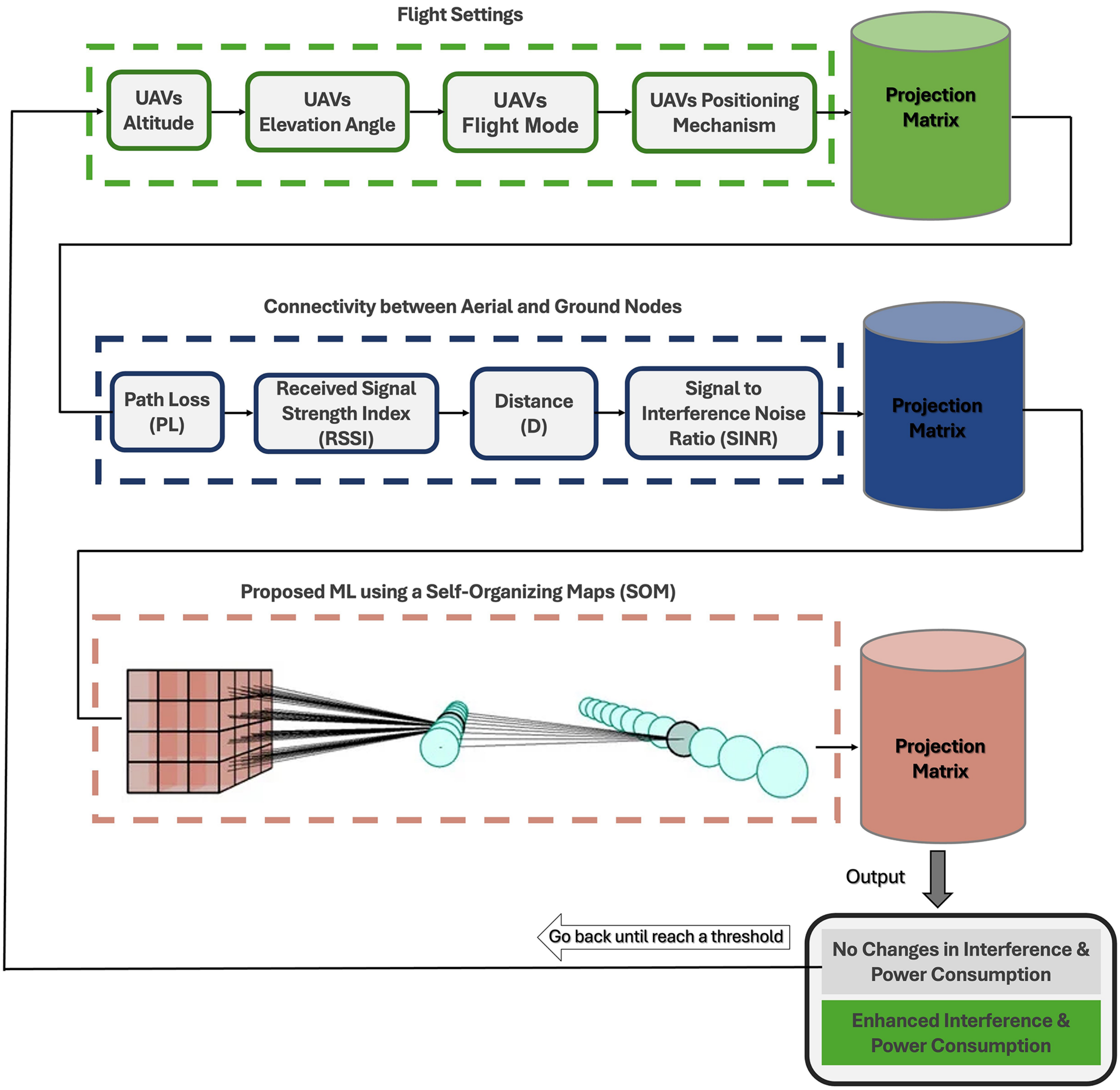



**Fig. 2** The three-phase flowchart of the proposed framework

where $I_{route}$ refers to the interference value of the route, $I_k$ is aggregate interference incurred by the receiver, $N_T$ refers to the thermal noise of the receiver, $I_D$ refers to the aggregate interference, $F(\theta)$ refers to the power flux density which is the measure of the strength of the radiation in the far field of each aerial platform according to $\theta$ above the horizontal plane, $G(\phi)$ refers to the antenna gain of mobile and/or fixed receivers in the direction of aerial platforms, $\lambda$ refers to the wavelength of the carrier, $L_{fr}$ refers to the feeder loss of mobile and/or fixed receivers, $I_G$ refers to the interference between aerial platforms and terrestrial nodes, $P_{HG}$ refers to the transmission power of aerial platforms, PL refers to the free-space pathloss from aerial platforms, $x_{ij}$ and $y_{ij}$ refers to the position of an aerial platform, r refers to the distance between the nadir of the aerial platforms and the terrestrial nodes, d refers to the distance between the aerial platforms stationed at different layers and altitudes, ij refers to cell location on the *x* axis and the *y* axis respectively, $G(\theta_{P-R})$ refers to the antenna gain with $\theta$ being the angle between aerial platforms and terrestrial nodes, $G(\theta_{R-P})$ refers to the antenna gain in reverse, $I_T$ refers to the total interference level, K refers

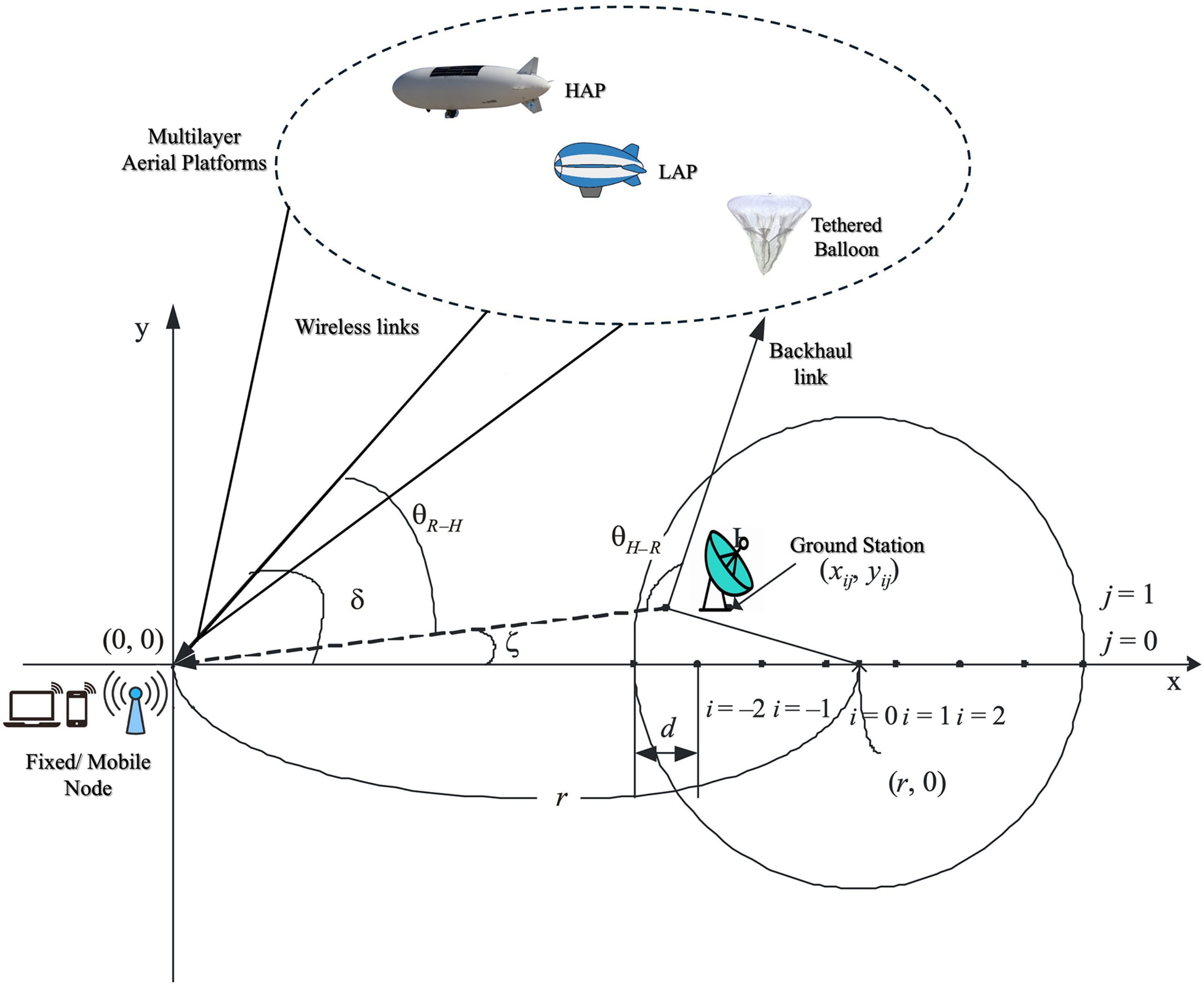



**Fig. 3** The positioning mechanism of the proposed framework

to the Boltzmann's constant, $\mathrm{T}$ refers to the temperature, $\mathrm{B}$ refers to the bandwidth, and $\mathrm{NF}$ refers to the noise figure of terrestrial nodes.

A performance indicator that helps with monitoring network connectivity and coverage, Received Signal Strength Index (RSSI), is calculated in Eq. (5) through to (8).

$$\mathrm{RSSI} = \mathrm{P_t} + \mathrm{h_t} + \mathrm{h_r} - \mathrm{PL} - \mathrm{L} \tag{5}$$

$$\mathrm{PL} = 92.5 + 20\mathrm{logd} + 20\mathrm{logf} \tag{6}$$

$$\mathrm{d} = 2\,\mathrm{E_r}[\cos^{-1}(\mathrm{E_r} \backslash \mathrm{E_r} + \mathrm{h_t} * cos\,(\theta)) - \theta\,] \tag{7}$$

$$\mathrm{SINR} = \mathrm{RSSI} \backslash \mathrm{N} + \mathrm{I} \tag{8}$$

where $\mathrm{P_t}$ refers to the transmitter power of aerial platforms, $\mathrm{h_t}$ refers to the altitude of aerial platforms, $\mathrm{h_r}$ refers to the receiver antenna height, $\mathrm{PL}$ refers to the free-space path loss, L refers to the system losses, d refers to the distance of transmission, $\mathrm{E_r}$ refers to the Earth's radius, $\theta$ is the elevation angle from a user's location, SINR refers to signal to interference and noise ratio, $\mathrm{N}$ refers to noise, and $\mathrm{I}$ refers to interference.

The ML component in the proposed framework is a SOM. In a SOM, neurons are arranged in a two-dimensional lattice, with each neuron being regarded as a cluster. Every neuron tries every input pattern and the chosen neuron from the input pattern becomes active. Additionally, in the process of adaptation, the winning neuron adjusts both itself and its neighbor neurons to predict how the patterns in the input dataset will be distributed. In the procedure of topological ordering of clusters, comparable clusters are then arranged side by side to enable quick detection of both distinct and similar clusters. If the number of clusters must be specified, this can be done by executing the algorithm with different cluster counts and choosing the best clustering

**Table 1** Sample input data set

| Platform | Altitude | Elevation | Path | GPS | RSSI | SINR |
|---|---|---|---|---|---|---|
| Tethered Balloon | 0.5 km | 0–15° | LoS = 1, NLoS = 0 | 21.437273, 40.512714 | -53dBm | 6.8dB |
| LAP | 3 km | 15°-30° | LoS = 1, NLoS = 0 | 21.437262, 40.515396 | -59dBm | 7.4dB |
| HAP | 17 km | 30°-90° | LoS = 1, NLoS = 0 | 21.437273, 40.512714 | -75dBm | 11dB |

outcomes based on the merits that are presented [31, 32]. The SOM algorithm is expressed in Eq. (9) through to (12).

$$X = [X_1, X_1, \ldots, X_m]^T \tag{9}$$

$$W_j = [W_{j1}, W_{j2}, \ldots, W_{jm}]^T, j = 1, 2, ..., I \tag{10}$$

$$i(x) = \arg\min_j ||x - W_j||, j = 1, 2, ..., I \tag{11}$$

$$W_j(n+1) = W_j(n) + \eta(n) h_{ji}(n)(x - W_j(n)) \tag{12}$$

where $X$ refers to the dimension input space, $W_j$ refers to the synaptic weight of each neuron in the output layer, I refers to the total number of neurons, $i(x)$ refers to the best matching or winning neuron of input vector x, $W_j(n+1)$ refers to the updated weight of the winning neuron node that is closer to the Best Matching Unit (BMU), $W_j(n)$ refers to the weights of the output neurons, $\eta$ refers to the learning rate, and $h_{ji}$ refers to the topological neighbourhood.

The input matrix in Eq. (8) is populated with data generated from Eqs. (1)–(7). Table 1 shows a sample input data set. These inputs are initially equal in weight when commencing training of the SOM since they produce similar effects. Thereafter, the weights may be updated to reduce the level of interference and power consumption to an acceptable threshold.

To validate the SOM results, the Levenberg-Marquardt algorithm and Mean Square Error (MSE) are used as in Eqs. (13) and (14).

$$xk + 1 = xk - [JTJ + \mu J] - 1JTe \tag{13}$$

$$MSE = \frac{1}{N}\sum (y - y')^2 \tag{14}$$

where $xk + 1$ refers to the updated Levenberg-Marquardt algorithm, $JTJ$ refers to an approximated Hessian matrix, $J$ refers to a Jacobian matrix, $\mu$ refers to the number of iterations, $e$ refers to a vector of network errors, $N$ refers to the number of data points, y refers to the actual value, and $y'$ refers to a predicted value.

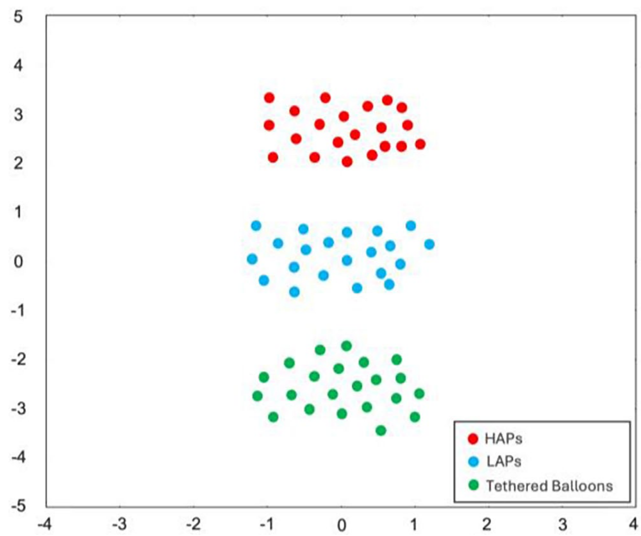



**Fig. 4** 2D distribution of aerial platforms in a multilayer fleet

## 4 Simulation and predictions

This section presents the predicted performance results of the proposed ML framework in relation to mitigation of interference, reduction of power consumption, and network connectivity. Thenceforth, a proof-of-concept smart IoT application in agriculture validates the proposed framework using Energy per bit to Noise (Eb/No) Spectrum Density, and Bit Error Rate (BER) as QoS indicators.

Our simulations use the 5G MIMO antenna specifications that has been provided by Airspan mobile Telecom Company [33]: frequency band of 10 GHz, transmitter power of 41dBm, antenna gain of 27dBi, diversity gain of 5dBi, transmitter sensitivity of -90dBm, losses of 3.5dB, receiver power of 18dBm, antenna gain of 3dBi, diversity gain of 2dBi, receiver sensitivity of -88dBm, losses of 0.5dB, bandwidth of 20 MHz, HAP altitudes between 17 and 20 km, LAP altitudes between 1 and 5 km, tethered balloon altitudes > 1 km, and elevation angle between 5° and 80° at different altitudes of an aerial platform.

Figure 4 is a 2D distribution in MATLAB of the aerial platforms within their own cluster, i.e. HAP, LAP, and Tethered Balloon clusters, in our multilayer fleet. This is the aerial testbed for the proposed framework. Each platform will change its position approximately 20 times within its allowable altitudes and with each change, a new interference value is calculated and then mitigated.

The distribution of Total Interference ($I_T$), firstly, as a function of the Final Distribution Point (FDP), and, secondly, in relation to θ and ϕ of terrestrial receivers is shown on Figs. 5 and 6 respectively. Interference mitigation scores best result at FDP 8.3, which reflects the effectiveness of our positioning mechanism. The values of the elevation angle reveal a reasonable increase that floats between a low bound of 5 and an upper bound of 15dB, with the highest value within the bounds achieved at an elevation angle of 30°. The highest value would be suitable for wireless coverage for all types of environments whether urban, suburban, or rural. Values above the upper bound are regarded as wasted transmitter power. Furthermore, the RSSI would also be a good indicator of the effectiveness of the positioning approach in achieving the best possible reception and coverage and in turn managing interference and power consumption. RSSI predictions pre- and post-optimization in relation to the distance of terrestrial receivers are shown on Fig. 7. The post-optimization prediction outperforms the pre-optimized prediction by an average of -14dBm. This represents a 16% improvement. Since RSSI is linked to path loss, post-optimization predictions suggest improved wireless connectivity with minimal attenuated signal, which helps with reducing power consumption.

The performance of the adopted SOM approach is evaluated by considering, firstly, the data clusters that have evolved and, secondly, the MSE before and after optimisation over hundreds of iterations. The results are visualised on Figs. 8 and 9 respectively. The network clusters its data into three aerial platform groups, i.e. HAPs, LAPs, and Tethered Balloons. Each group is visualized as a set of data point locations and associated weight vectors with each data point connecting to a neuron as input. The map is well distributed throughout the resulting input space, with the connection patterns of the inputs being comparable, thus, highly correlated. The MSE evaluates the training, testing, and validation phases for both the non-optimized and optimised approaches. The optimized result is relatively small which indicates that there has been no overfitting and, overall, the optimized approach yields improved accuracy compared to the non-optimized.

A proof-of-concept smart IoT application in agriculture has been developed to showcase the integration of sensor technology, aerial platforms and IoT into all agricultural operations and most importantly the effectiveness and efficiency of the proposed framework. Figure 10 shows this proof-of-concept in a smart agriculture context. The figure visualizes a bird's-eye view of the conceptual setup that consists of sky and ground segments. The sky segments depict the multilayer fleet of aerial platforms being equipped with a variety of devices, cameras, and communication payloads to enable connection with the wireless

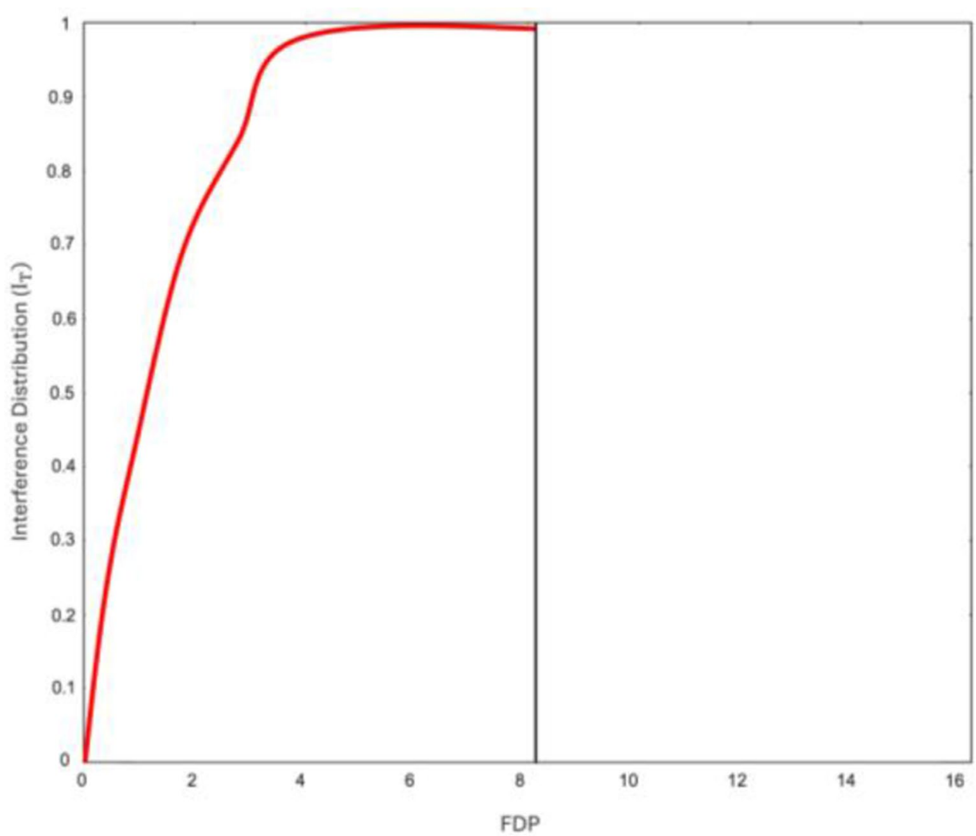



**Fig. 5** Interference distribution of $I_T$ as a function of FDP

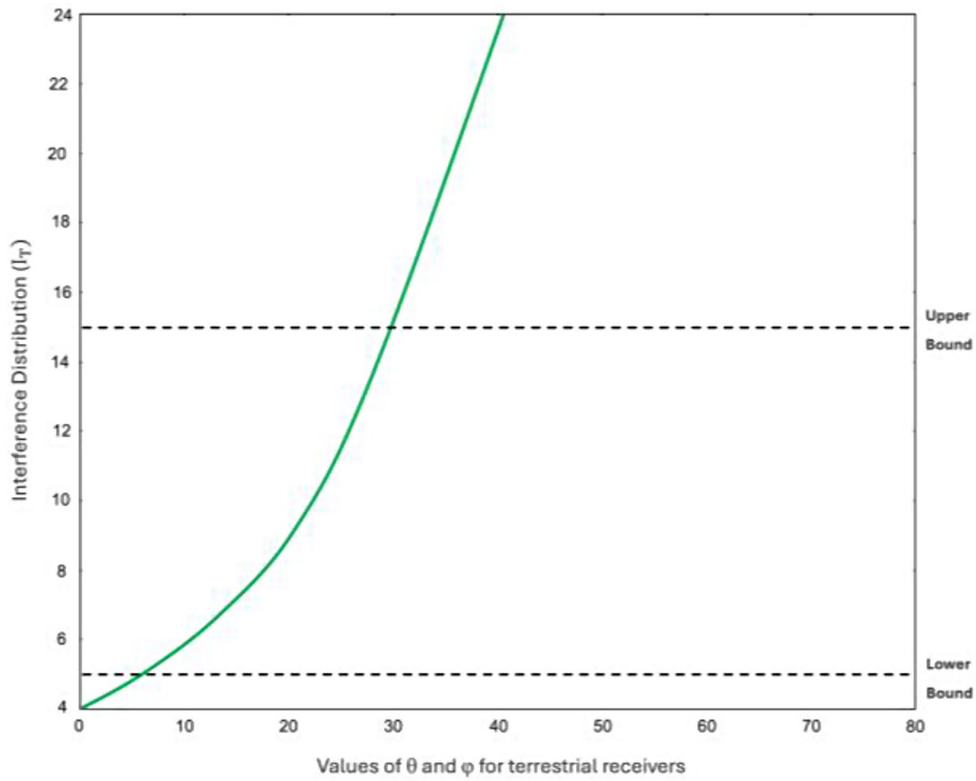



**Fig. 6** Interference distribution of $I_T$ in relation to θ and ϕ of terrestrial receivers

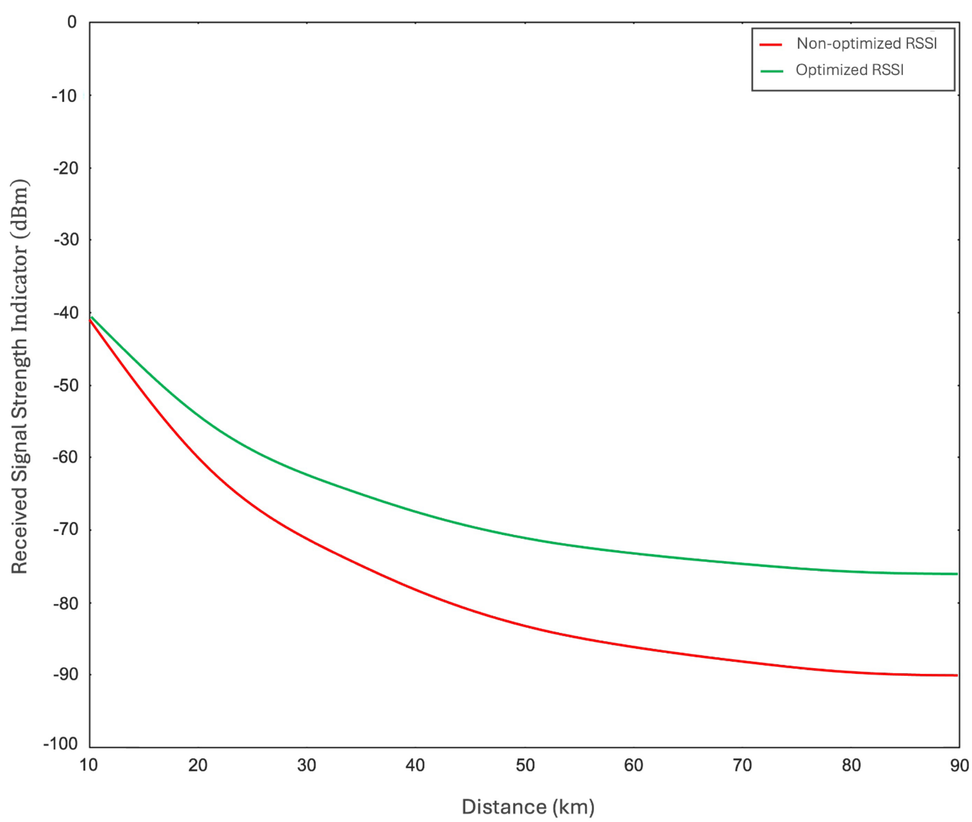



**Fig. 7** Optimized vs. non-optimized RSSI

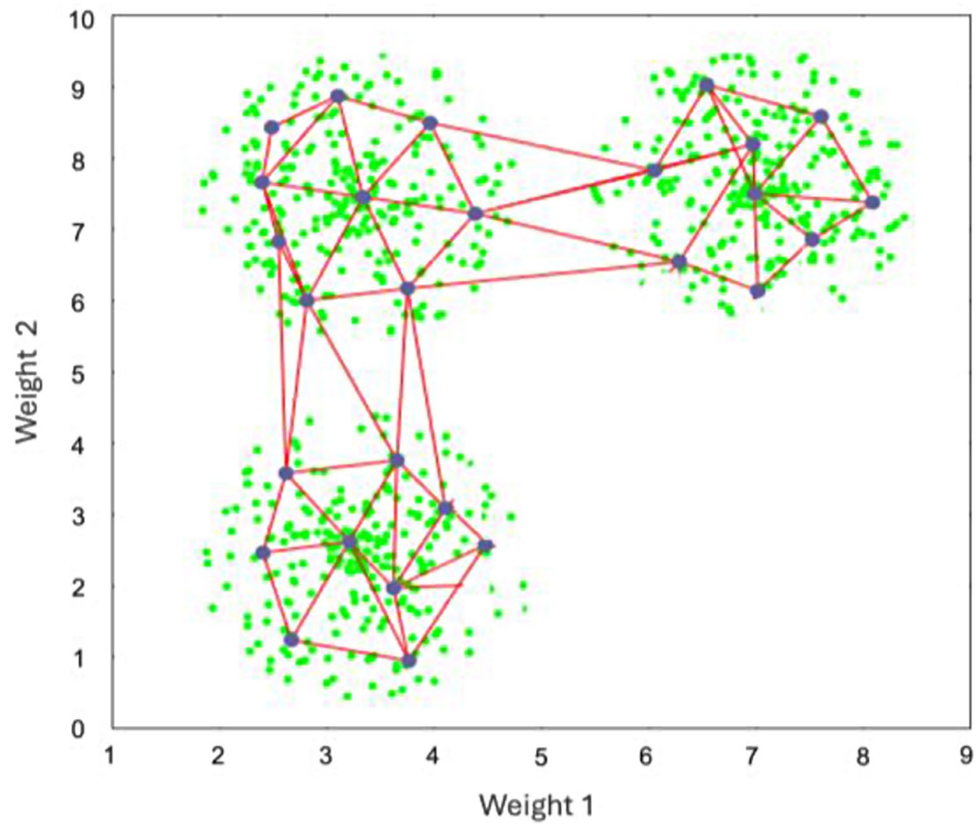



Fig. 8 Data clustering

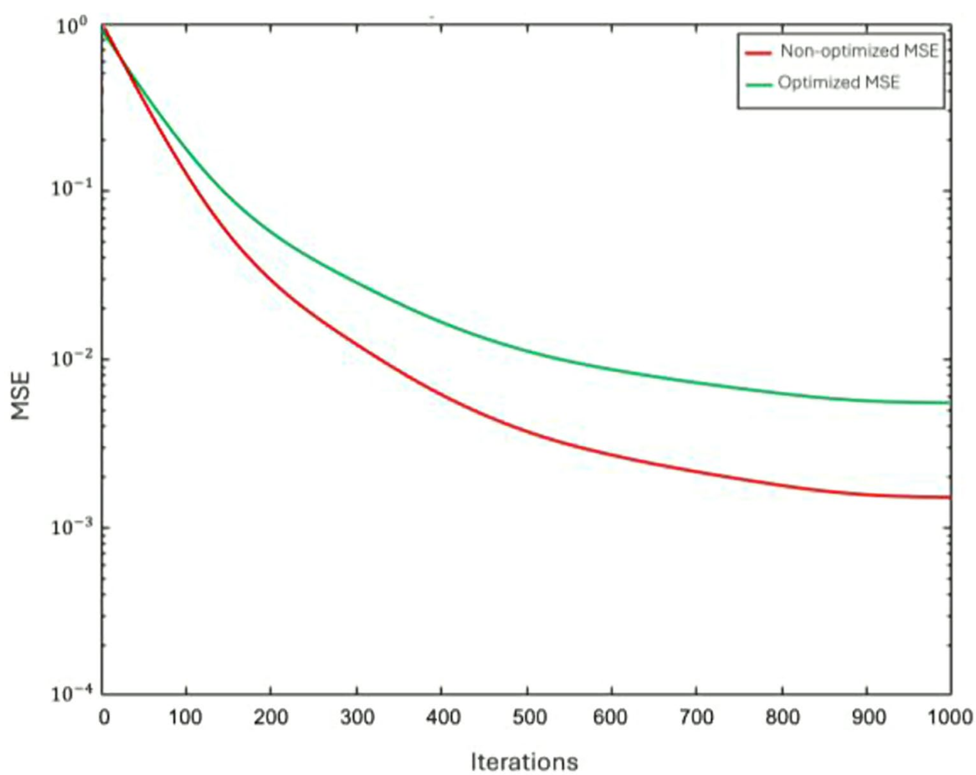



Fig. 9 MSE

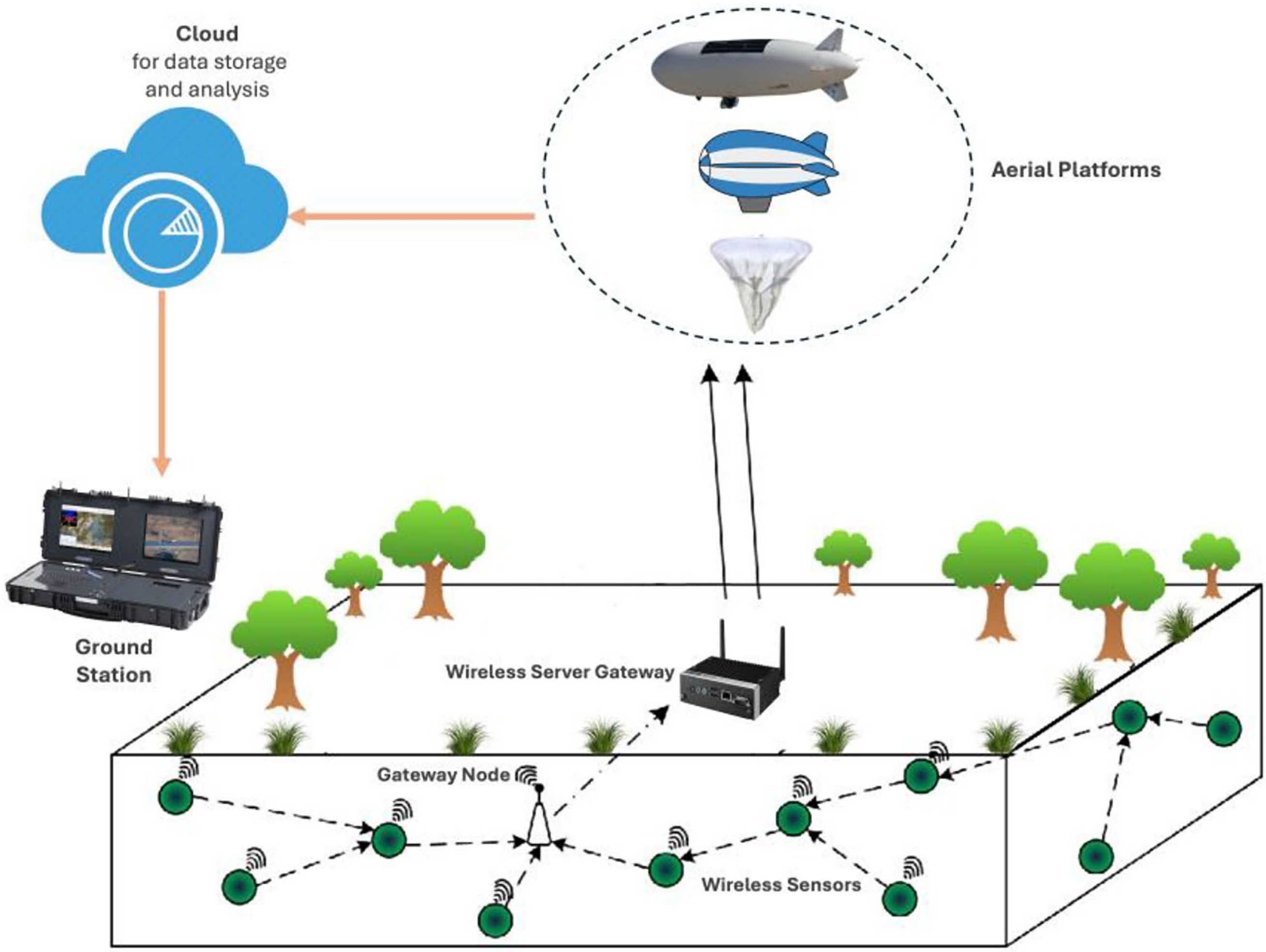



**Fig. 10** A bird's-eye-view of the proof-of-concept IoT app in a smart agricultural context

server gateway and to collect data. The data is transferred to the cloud for storage and analysis. The ground segment consists of underground and overground sensors for measuring temperature, humidity, water levels, and soil moisture with a gateway node serving as a mediator between the sensors and the wireless server gateway and the ground stations for command-and-control.

Power consumption and interference are closely coupled in wireless communication systems. Increasing power consumption to guarantee signal strength leads to an increase in interference. Lowering transmission power can reduce both power consumption and interference. However, this can lead devices into sleep mode, which in turn would make them susceptible to interference when they return to normal transmission mode. Therefore, to overcome this and maintain signal strength for a clear reception with minimum interference, a delicate balance using an optimization approach is needed [34–38].

Figure 11 presents a step-by-step flowchart on the execution of the proof-of-concept in a smart agriculture context. During the first step, sensors sense farm data every 60 min. During the second step, this data is stored temporarily on the wireless server gateway. During the third step, the aerial platforms regularly retrieve the data from the wireless server gateway. During the fourth step, the data retrieved is sent to the cloud for storage and analysis. This process helps with automating a set of actions for precision and sustainable agriculture, which, in turn can increase crop production, and help with preservation of natural resources.

Figure 12 shows the component devices of the proof-of-concept IoT application in a smart agriculture context. Figure 12 (a) shows real images of the sensors that sense water level, soil moisture, temperature and humidity and connect to a Microcontroller Raspberry Pi 4. Figure 12 (b) shows real images of the deployment of these sensor devices in a smart agriculture context.

Figure 13 presents a dashboard developed using the Blynk IoT tool that displays real-time data generated by the sensors in March 2024. The data helps with making

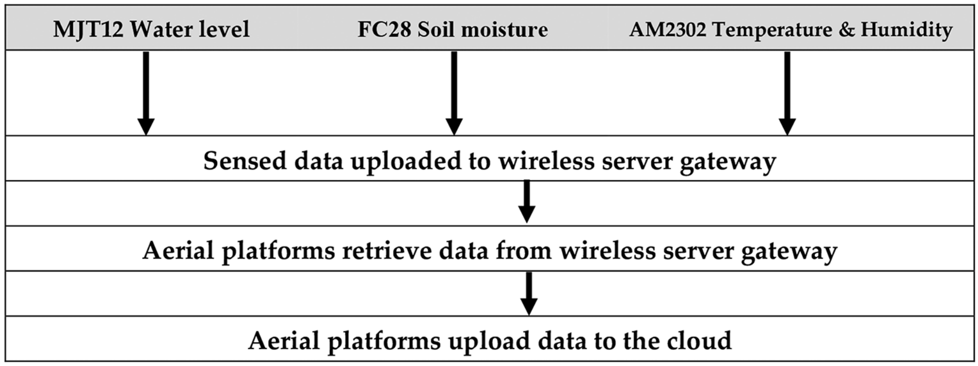



**Fig. 11** Flowchart on executing the proof-of-concept in a smart agriculture context

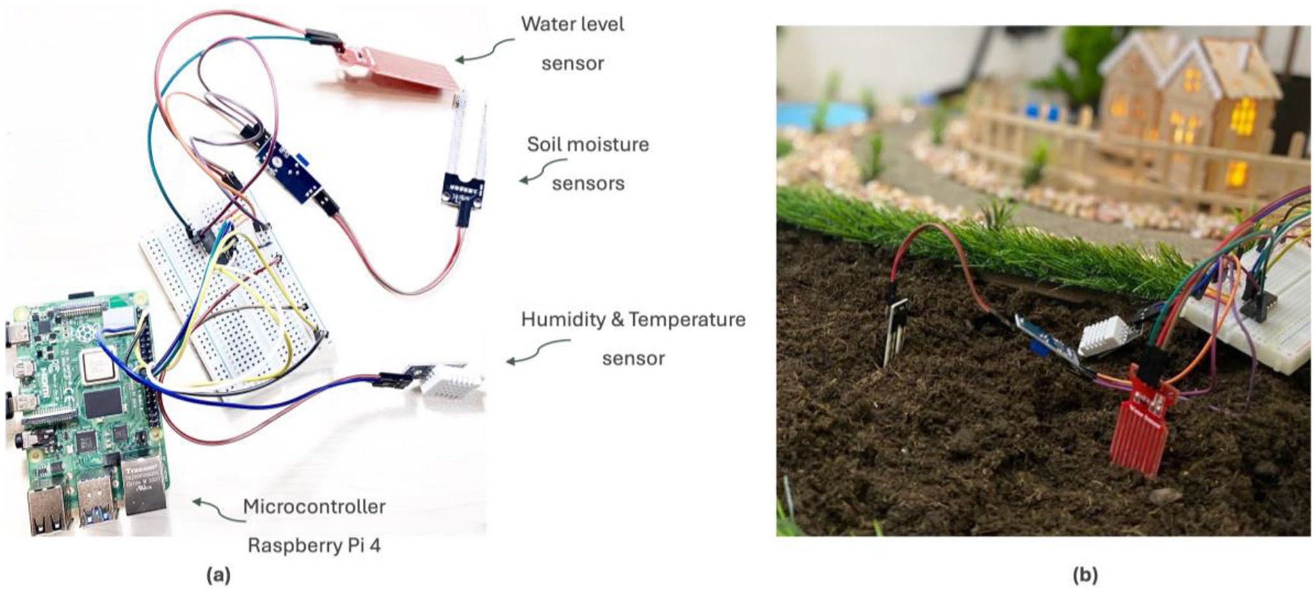



**Fig. 12** Implementation of a proof-of-concept IoT app in a smart agriculture context

informed decisions on irrigation based on real evidence of need, thus preserving precious water resources.

The communication links between the aerial platforms and the ground sensors are evaluated for power consumption optimality following each data uplink using the two QoS indicators, BER and Eb/No. When the values of the two QoS indicators decrease, the wireless link performance rises which indicates a channel with low error rates and thus a minimum transmission power within the same coverage range. At the lowest BER of $10^{-8}$, the optimized outperforms the non-optimized by 6dB. Furthermore, optimizing the RSSI when managing interference helps with reducing power consumption and making energy efficiencies. The predicted BER against the Eb/No values and the predicted energy efficiency against the RF chain values for non-optimised and optimised power consumption are shown on Figs. 14 and 15 respectively.

To validate the SOM results, we use the regression plotting tool of the MATLAB NN to track the MSE. During the initial stage of training, the SOM is trained with training data sets upto a maximum number of iterations (epochs). Once the training is complete, the training data sets are substituted with the real data sets and the stages of validation and testing commence. Figure 16 tracks the decrease of MSE during validation and testing. The best validation performance is produced during epoch 12 since:

- the MSE result is the lowest for 18 epochs,
- testing and validation performances remain relatively unchanged between epochs 10–13, and.
- overfitting begins to manifest after epoch 13.

## 5 Concluding discussion

Evidently, unmanned aerial platforms are playing a vital role in bridging the coverage gap in remote regions, including farmland [39–41]. Such aerial platforms offer a unique perspective from above, which can be deployed for collecting data, monitoring infrastructure, environmental surveillance,

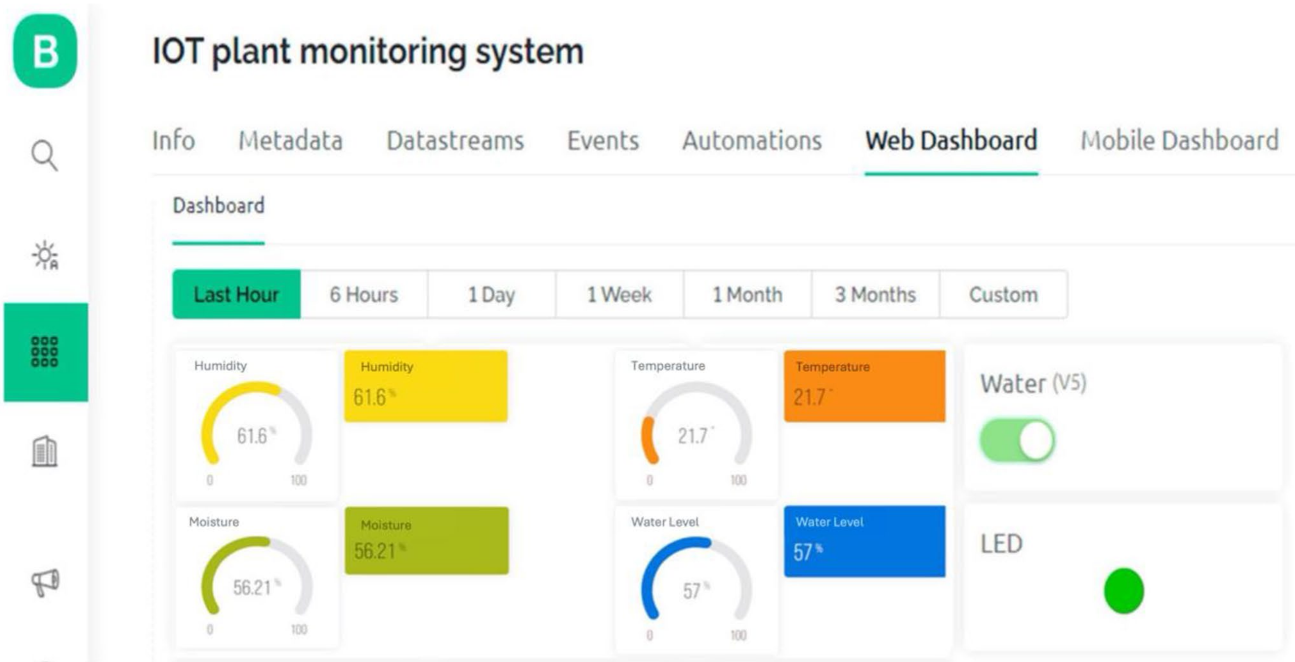
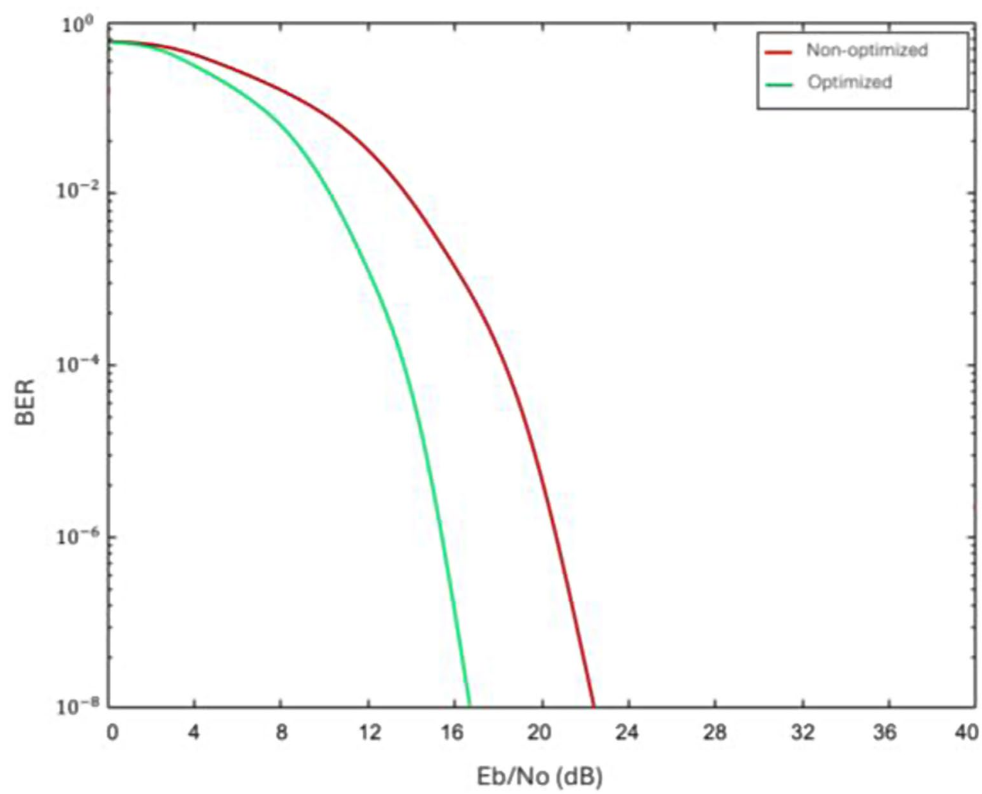



**Fig. 13** Dashboard with real-time data generated by the sensors

**Fig. 14** BER versus Eb/No for optimized against non-optimized power consumption




and last-mile connectivity. However, such a fleet of platforms will likely result in increased interference and power consumption.

The integration of AI and Simulation is old wine [42] in new bottles [43] with sustainability now dominating the green agenda. This work presents a framework that integrates ML with a fleet positioning mechanism to mitigate interference, and reduce power consumption, which is an added value for sustainability and long endurance in the air. The actual results and predictions of the proof-of-concept

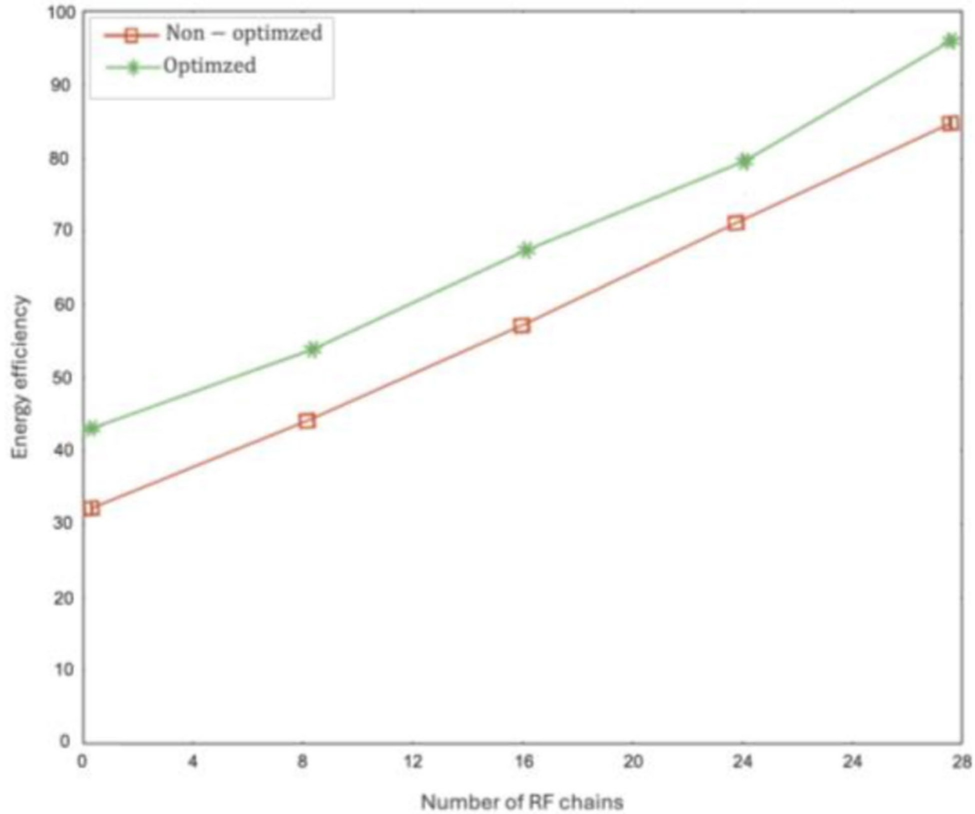



**Fig. 15** Energy efficiency versus RF chains for optimized against non-optimized consumption

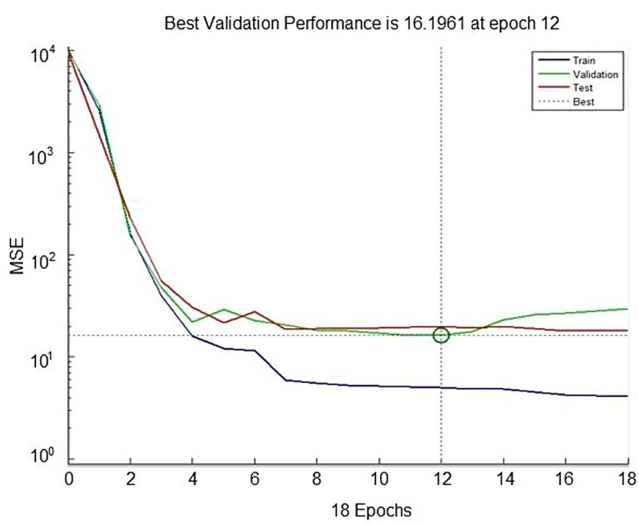



**Fig. 16** SOM validation

verify that the post-optimization RSSI outperforms the pre-optimization RSSI by 16%.

This work can be extended to proof-of-concept applications in smart cities, such as waste management and emergencies [44]. Furthermore, extending the framework to include, for example, CubeSats at the much higher altitude of 400 km will add the potential for new types of smart IoT applications such as fleet tracking [45].

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**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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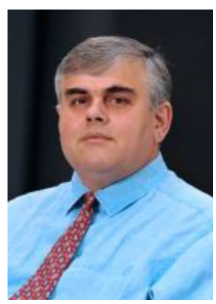

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