Robust Indoor Localisation for Swarm UAVs: An Adaptive Exponential Weighted Centroid Approach

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***Abstract*— Precise indoor localisation is essential for swarm unmanned aerial vehicles (UAVs) operating in GPS-denied and congested environments. We propose a low-cost Received Signal Strength Indicator (RSSI)-based localisation framework for resource-constrained platforms. The Relative-span Exponential Weighted Localisation (REWL) technique extends Weighted Centroid Localisation (WCL) by introducing adaptive exponential weighting to reduce the influence of weak and noisy RSSI measurements. Empirical indoor experiments compare REWL against Min–Max, trilateration, and WCL using Arduino Nano ESP32 units deployed on Robolink CoDrones in a controlled environment. Results show a substantial reduction in localisation error, a high coefficient of determination of $R^2 = 0.9723$, and a lower fitted path-loss exponent, indicating improved stability under the tested conditions. The low computational overhead of REWL supports real-time embedded localisation and scalable multi-UAV deployments.**

Keywords: Indoor Localisation, GPS-Denied, Swarm UAVs, Signal Strength, Trilateration and Path-loss exponent.

I. INTRODUCTION

Swarms of unmanned aerial vehicles (UAVs) require precise indoor localisation and coordination around known anchors, as illustrated in Fig. 1 whereas all acronyms used in this paper are summarised in Table I. Accurate positioning relative to fixed anchor nodes with known coordinates is essential for applications operating in GPS-denied environments [1]–[3], including tracking individuals in smart homes, hospitals, and commercial buildings [4]–[5], monitoring robots or personnel at construction or railway sites [6], and enabling precise control in inspection, navigation, and safety systems [7]. Indoor localisation faces significant challenges due to signal attenuation, blockage, and multipath propagation. Multipath occurs when a transmitted signal reaches the receiver through multiple paths caused by reflections, diffraction, and scattering from walls, furniture, and other indoor objects. As a result, several delayed and attenuated copies of the same signal arrive at the receiver with different phases and amplitudes, leading to constructive and destructive interference. This phenomenon distorts the measured signal parameters and introduces substantial positioning errors. Common indoor localisation methods include Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Received Signal Strength Indicator (RSSI). AoA-based methods are particularly sensitive to multipath because reflected signals can alter the perceived arrival angle, reducing angular estimation accuracy. ToA and TDoA techniques require precise time synchronisation between transmitters and receivers, which increases system complexity and cost [8-12]. RSSI-based localisation is comparatively economical and easy to deploy; however, it is highly susceptible to multipath fading and shadowing effects in indoor environments, which degrade reliability and accuracy [13-16]. Furthermore, studies [17-19] highlight that human movement, environmental dynamics, and the assumption of static conditions further limit localisation performance.

This work evaluates Min-Max, Trilateration, Weighted Centroid Localisation (WCL), and our Relative-span Exponential Weighted Localisation (REWL) technique, deploying REWL on Arduino Nano and CoDrone for precision assessment. Furthermore, this research provides the following research contributions:

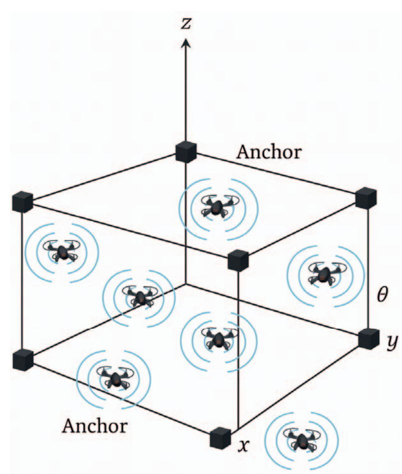

Fig. 1. Indoor Localisation and Coordination of UAVs.

- First, we analysed four widely adopted RSSI-based localisation techniques (Min–Max, Trilateration, WCL, and REWL) through a comparative study of their theoretical foundations and practical limitations in indoor

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TABLE I
ACRONYMS AND FULL FORMS

Acronym	Full Form
2D	Two-Dimensional
3D	Three-Dimensional
AoA	Angle of Arrival
ESP-NOW	Espressif connectionless peer-to-peer wireless protocol
ESP32	Espressif Systems 32-bit Wi-Fi SoC microcontroller
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
MAC	Media Access Control
MCU	Microcontroller Unit
REWL	Relative-span Exponential Weighted Localisation
RSSI	Received Signal Strength Indicator
TDoA	Time Difference of Arrival
ToA	Time of Arrival
UAV	Unmanned Aerial Vehicle
WCL	Weighted Centroid Localisation

environments.

- Secondly, we evaluated the REWL algorithm using a small-sized Arduino Nano for localisation under static and non-human-influenced environments.
- Finally, we deployed the proposed board over Robolink's CoDrone UAVs in a controlled indoor setting to acquire their positions.

The remainder of this manuscript is organised as follows. Section II presents the received signal strength indicator (RSSI)-based localisation approaches considered in this study, including the Min–Max, Trilateration, WCL, and the proposed REWL techniques. Section III describes the empirical evaluation, detailing the experimental design, hardware configuration, and data collection procedures. Section IV reports the results and provides a comprehensive technical discussion of the observed performance. Finally, Section V concludes the paper and outlines future research directions.

II. RSSI-BASED LOCALISATION APPROACHES

This ongoing project utilises an RSSI-based localisation system that includes a computer-connected base station, referred to as the ground station, three reference nodes at predetermined locations, and an unidentified target node. The base station is interfaced with a laptop-class computer that functions as a control and data-processing unit. Specifically, the computer initiates beacon exchanges, aggregates RSSI measurements received via the base station, and executes the path-loss-based distance estimation and localisation algorithms:

$$\mathrm{RSSI}_d = \mathrm{RSSI}_{d_0} - 10\beta \log_{10}\left(\frac{d}{d_0}\right) \tag{1}$$

$$d = 10^{\frac{\mathrm{RSSI}_{d_0} - \mathrm{RSSI}_d}{10\beta}}, \quad d_0 = 1\,\mathrm{m} \tag{2}$$

where β is the path-loss exponent, RSSI_{d_0} is the reference RSSI at distance d_0. In the third process, the localisation methods Min–Max, trilateration, WCL, and REWL are applied. These methods were chosen for their low complexity and good estimation performance as validated in prior works [12-16], And we provide summary of each below.

A. Min-Max Method

The Min–Max or bounding-box method [16] constructs a bounding box for each reference node based on the distance estimates and determines the intersection box. The estimated position (x_{est}, y_{est}) is calculated as:

$$\mathrm{xmin} = \max(x_1 - d_1, x_2 - d_2, x_3 - d_3) \tag{3}$$

$$\mathrm{xmax} = \min(x_1 + d_1, x_2 + d_2, x_3 + d_3) \tag{4}$$

$$\mathrm{ymin} = \max(y_1 - d_1, y_2 - d_2, y_3 - d_3) \tag{5}$$

$$\mathrm{ymax} = \min(y_1 + d_1, y_2 + d_2, y_3 + d_3) \tag{6}$$

$$\mathrm{x}_{est} = \frac{\mathrm{xmin} + \mathrm{xmax}}{2} \tag{7}$$

$$\mathrm{y}_{est} = \frac{\mathrm{ymin} + \mathrm{ymax}}{2} \tag{8}$$

Here, (x_i, y_i) for $i = 1, 2, 3$ denote the known coordinates of the reference (anchor) nodes, and d_i represents the estimated distance between the unknown target node and each corresponding reference node.

B. Trilateration Method

The trilateration method [19] determines the target position (x_{est}, y_{est}) as the intersection point of three circles with radii d_1, d_2, d_3, solving:

$$(x_{est} - x_1)^2 + (y_{est} - y_1)^2 = d_1^2 \tag{9}$$

$$(x_{est} - x_2)^2 + (y_{est} - y_2)^2 = d_2^2 \tag{10}$$

$$(x_{est} - x_3)^2 + (y_{est} - y_3)^2 = d_3^2 \tag{11}$$

C. Weighted Centrolid localisation Method

Another method is WCL [19], which enhances the basic centroid localisation by assigning higher weights to closer reference nodes. The estimated coordinates are given in equations (12-14), where g is a tunable parameter, typically set to 1.

$$x_{est} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} = \frac{w_1 x_1 + w_2 x_2 + w_3 x_3}{w_1 + w_2 + w_3} \tag{12}$$

$$y_{est} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} = \frac{w_1 y_1 + w_2 y_2 + w_3 y_3}{w_1 + w_2 + w_3} \tag{13}$$

$$w_i = \frac{1}{d_i^g} \tag{14}$$

Here, (x_i, y_i) are the coordinates of the i^{th} reference node, d_i is its distance to the target, w_i is the assigned weight, n is the number of reference nodes, and g controls the weighting effect.

D. Relative Span Exponential Weighted Localisation Method

REWL modifies WCL by exponentially weighting anchors with factor α (0.10–0.20) using the maximum RSSI. Weights:

$$w_i = (1 - \alpha)^{\mathrm{RSSI}_{\max} - \mathrm{RSSI}_i}.$$

This adaptive mapping boosts reliable anchors, suppresses noisy ones, improves conditioning, smooths estimates, and

TABLE II

STATE-OF-THE-ART RSSI LOCALISATION APPROACHES AND LIMITATIONS

Approach	Strengths	Limitations	Human Movement
AoA	Good accuracy in open environments	Sensitive to multipath, unsuitable indoors [15]	No
ToA/TDoA	High positioning accuracy	Needs tight synchronization, costly [15]	No
RSSI (General)	No extra hardware, cost-effective [11]	Unstable signals indoors, fluctuating [16]	Partial
Min–Max	Simple, low-complexity [14]	Sensitive to RSSI variations [17-18]	Some studies
Trilateration	Good under ideal conditions [9] [17]	Prone to noise and multipath errors [18]-[19]	Some studies
WCL	Stable with RSSI weights	Suffers under rapid fluctuations	Rarely considered
REWL	Better tolerance to RSSI changes	Higher computational cost	Rarely considered

TABLE III

KEY LIMITATIONS OF CLASSICAL RSSI LOCALISATION METHODS

Method	Principal Limitations
Min–Max (Bounding Box)	Coarse region; range-error sensitive; empty/oversized boxes; center bias; corner drift with uneven anchors.
Trilateration	Requires accurate intersections; RSSI noise ill-conditions solve; nonlinear/iterative burden on MCUs; needs LS/regularization for stability.
Weighted Centroid (WCL)	Edge/density bias; environment-specific exponent g; similar RSSIs $\Rightarrow$ near-uniform weights and low accuracy.

yields 25–40% Mean Square Error (MSE) reduction with $R^2 = 0.9723$.

$$x_{\text{est}} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \tag{15}$$

$$y_{\text{est}} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}. \tag{16}$$

For completeness, the 3D extension of REWL follows directly as:

$$z_{\text{est}} = \frac{\sum_{i=1}^{n} w_i\, z_i}{\sum_{i=1}^{n} w_i}, \tag{17}$$

where z_i denotes the height of the ith reference node. In this study, all anchors were placed at approximately the same altitude ($z_i \approx 2.2\,\text{m}$), so the localisation problem reduces to the two-dimensional case considered above. REWL employs an adaptive exponential weighting rule that emphasises stronger RSSI links and suppresses weaker, noisier measurements. Since it relies on relative RSSI differences, REWL avoids matrix inversion and iterative optimisation, resulting in low computational overhead suitable for resource-constrained platforms such as the Arduino Nano ESP32. Section IV provides an experimental comparison with Min-Max, Trilateration, and WCL, while Table II outlines the current state of localisation methodologies along with their limitations, and Table III summarises the primary constraints of traditional RSSI localisation techniques.

E. Analytical Justification

We analyse the first-order sensitivity of the weighted centroid estimator to perturbations in RSSI measurements. Let the estimated position be defined as

$$\hat{\mathbf{p}} = \frac{\sum_{i=1}^{n} w_i\, \mathbf{p}_i}{\sum_{i=1}^{n} w_i}, \qquad w_i > 0,$$

where $\mathbf{p}_i$ denotes the position of the ith anchor and w_i represents its associated weight. For small RSSI deviations δr_i around nominal values r_i, a first-order Taylor expansion yields

$$\delta\hat{\mathbf{p}} \approx \sum_{k=1}^{n} \Big(\frac{\partial \hat{\mathbf{p}}}{\partial r_k}\Big)\delta r_k \tag{18}$$

$$= \sum_{k=1}^{n} \frac{w_k}{\sum_j w_j} \underbrace{(\mathbf{p}_k - \hat{\mathbf{p}})}_{\text{centroid leverage}} \underbrace{\frac{\partial \ln w_k}{\partial r_k}}_{\text{weight sensitivity}} \delta r_k. \tag{19}$$

Equation (19) shows that the mean-square error (MSE) is governed by two principal factors:

1) Centroid leverage $\frac{w_k}{\sum_j w_j}\|\mathbf{p}_k - \hat{\mathbf{p}}\|$, which increases when an anchor exerts stronger geometric influence on the estimate.

Weight sensitivity, defined as $\partial \ln w_k / \partial r_k$, quantifies the responsiveness of the weighting scheme to RSSI fluctuations; minimising this term reduces the propagation of measurement noise into the final position estimate.

2) For WCL, the weighting function $w_k = d_k^{-g}$ is combined with the log-distance path-loss model $r_k = r_0 - 10\beta \log_{10}(d_k/d_0)$, yielding $d_k = d_0\, 10^{(r_0 - r_k)/(10\beta)}$ and $\partial(\ln d_k)/\partial r_k = -\ln 10/(10\beta)$. Consequently, the weight sensitivity becomes

$$\frac{\partial \ln w_k}{\partial r_k} = g\, \frac{\ln 10}{10\beta}, \tag{20}$$

indicating that RSSI perturbations are linearly transferred to the weights regardless of anchor distance. Equation (20) indicates that WCL exhibits constant weight sensitivity independent of distance. Consequently, RSSI perturbations are transmitted almost uniformly to all anchors, including weak or distant ones, which can degrade localisation stability.

F. REWL (Exponential RSSI Weighting)

In REWL, the anchor weights are computed as $w_k = (1-\alpha)^{(r_{\max} - r_k)}$, where $0 < \alpha < 1$ regulates the exponential decay relative to the strongest observed RSSI $r_{\max}$, and r_k denotes the RSSI measured from the kth anchor. This exponential mapping assigns substantially larger weights to anchors with stronger RSSI, while rapidly attenuating the influence of weaker (and typically noisier) measurements. As a result, the localisation estimate is driven primarily by higher-quality anchors. Taking logarithms and differentiating with respect to r_k gives

$$\frac{\partial \ln w_k}{\partial r_k} = \frac{\partial\big[(r_{\max} - r_k)\ln(1-\alpha)\big]}{\partial r_k} = -\ln(1-\alpha) \approx \alpha,$$

where the approximation holds for practical values $\alpha \in [0.1, 0.2)$. Therefore, anchors with low RSSI receive exponentially small w_k, which directly reduces their centroid leverage $\frac{w_k}{\sum_j w_j}$. REWL consequently decreases both (i) the weight sensitivity to RSSI fluctuations (through α) and (ii) the contribution of unreliable anchors (through exponential suppression), yielding a compounded reduction in estimation variance. Combining Eq. (19) with the above result yields an anchor-wise bound on the mean-square error contribution:

$$\mathbb{E}\big[\|\delta\hat{\mathbf{p}}\|^2\big] \lesssim \sum_k \left(\frac{w_k}{\sum_j w_j}\right)^2 \|\mathbf{p}_k - \hat{\mathbf{p}}\|^2 \left(\frac{\partial \ln w_k}{\partial r_k}\right)^2 \sigma_r^2. \quad (21)$$

Using Eq. (20), the anchor-level sensitivity ratio between REWL and WCL can be expressed as

$$\frac{\mathrm{Sens}_{\mathrm{REWL},k}}{\mathrm{Sens}_{\mathrm{WCL},k}} \approx \frac{\left(\frac{w_k^{\mathrm{REWL}}}{\sum_j w_j^{\mathrm{REWL}}}\right)^2}{\left(\frac{w_k^{\mathrm{WCL}}}{\sum_j w_j^{\mathrm{WCL}}}\right)^2} \left(\frac{\alpha}{g\,\frac{\ln 10}{10\beta}}\right)^2. \quad (22)$$

REWL exponentially downweights weak anchors, reducing leverage so eq. (21) stays below 1 for $\alpha \approx 0.1$–0.2. By concentrating weight on high-RSSI anchors (higher SNR, lower variance), it lowers the effective variance in eq. (20).

III. Empirical Evaluation

In this work, four identical Arduino Nano ESP32 units were designed and implemented, as depicted in Fig. 2. Three units were configured as fixed reference anchors and strategically deployed at known positions within the indoor environment, as illustrated in Fig. 3, to establish the localization framework. The fourth unit, architecturally identical to the anchor nodes, was interfaced with the ground station and operated as the mobile target node. Its spatial coordinates were estimated relative to the deployed anchors using the proposed localization methodology. Within the Fig. 3, one may also see the MAC addresses of three anchor units that were acquired before delpoyment. The fourth unit functioned as the target during RSSI measurements and is not depicted. Algorithm 1 was employed to gather RSSI data for localisation. Figure 4 illustrates the recorded indoor dimensions, encompassing center, length, breadth, height, and diagonal, while Figure 5 depicts the arrangement of the units throughout the trial area. The hardware-to-maps approach is advantageous for wireless and IoT novices owing to its cost-effectiveness, energy efficiency, and minimal wiring requirements.

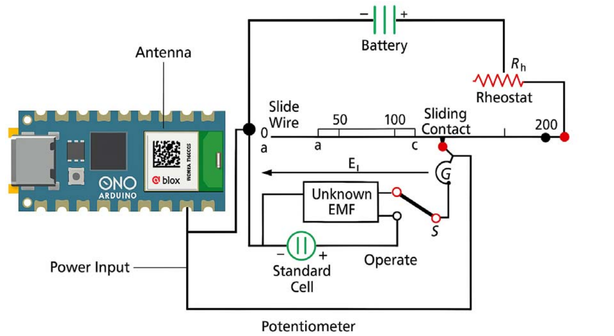

Fig. 2. Small Size Arduino Nano-based RSSI localisation Unit.

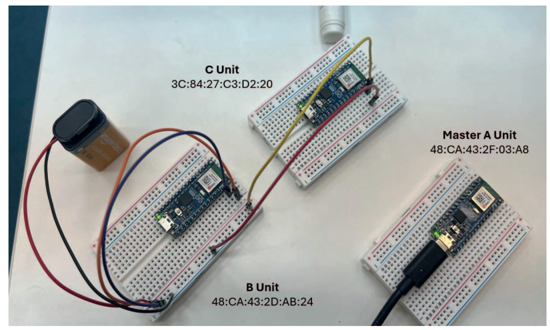

Fig. 3. Acquiring the MAC addresses for Arduino Nano Board units and RSSI values.

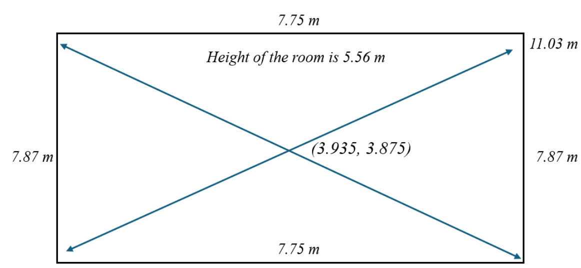

Fig. 4. Dimensions of the room where units are deployed.

Fig. 5. Deploying the small Arduino Nano Board units at different locations.

IV. Results and Discussions

The proposed REWL outperforms Min–Max, Trilateration, and WCL. In Fig. 6, integrated with Robolink's CoDrone as shown. REWL achieves the highest $R^2 = 0.9723$ and the

Algorithm 1 ESP32 Nano RSSI Scanner — Pseudocode

```
Input: None
Output: Printed list of nearby devices with MAC (BSSID)
        and RSSI (dBm)
Function Setup():
    Initialize serial at 9600 baud  while USB serial not
     connected do
      wait
    print "ESP32 Nano - RSSI Scanner" // Configure
       WiFi
    set WiFi mode ← STATION  disconnect any prior WiFi
     connection  delay 100 ms
Function Loop():
    while true do
        print "Scanning for nearby WiFi/ESP-NOW de-
         vices..."  n ← ScanNetworks(async = false,
         show_hidden = true)  if n == 0 then
            print "No devices found."
        else
            print n and " device(s) found:"  for i ← 0 to
             n − 1 do
                mac ← BSSIDstr(i) ; // Acquire MAC
                 address (BSSID)
                rssi ← RSSI(i) ;             // Signal
                 strength in dBm
                print (i+1), ". MAC: ", mac, " | RSSI: ",
                 rssi, " dBm"
        print "——————————————-" delay 5000
         ms ;          // Scan every 5 seconds
Setup() Loop()
```

lowest path-loss exponent $\beta = 2.131$, indicating superior signal stability as can see in Fig. 7 and 8. Fig. 8 validates Arduino Nano ESP32 trilateration indoors; Board A estimated at $(-2.22, -1.35, 2.21)$ m. Moreover, REWL achieves RMSE $0.31\,\mathrm{m}$, MAE $0.27\,\mathrm{m}$, $\sim 38\%$ MSE reduction vs. WCL, $> 50\%$ vs. Min–Max, and $\sigma = 0.08\,\mathrm{m}$ (WCL 0.14, Trilateration 0.20).

V. Conclusion and Future Directions

This research introduces an improved RSSI-based localisation framework for economical, lightweight UAVs operating in global positioning system GPS-denied environments. Four methodologies Min–Max, Trilateration, WCL, and the proposed REWL were implemented on Arduino Nano ESP32 modules using ESP-NOW. REWL achieved enhanced positioning performance, with $R^2 = 0.9723$, a path-loss exponent of $\beta = 2.131$, and a 38% reduction in mean-square error compared with WCL. The error metrics further validate robustness in static indoor evaluations, yielding an RMSE of 0.31 m, an MAE of 0.27 m, and the lowest standard deviation of $\sigma = 0.08$ m. By selectively prioritising higher-quality RSSI measurements, REWL mitigates multipath interference and signal variability while maintaining low computational overhead and embedded suitability. The straightforward implementation on Arduino-based CoDrone units demonstrates practical potential for immediate decentralised navigation and swarm coordination. Overall, the proposed methodology offers a reproducible and scalable foundation for economical indoor localisation research on embedded UAV platforms and supports real-world deployment. While this study focused on static indoor testing, future work should extend REWL to dynamic conditions involving human mobility, changing boundaries, and electromagnetic interference. Further improvements can be achieved through sensor fusion and adaptive RSSI filtering (e.g., IMU, barometer, UWB) to enhance spatial awareness under motion. Robustness should be evaluated over extended datasets capturing mobility effects. Additionally, deploying REWL in synchronised multi-UAV networks and validating real-time 3D localisation can improve cooperative swarm autonomy and indoor navigation reliability.

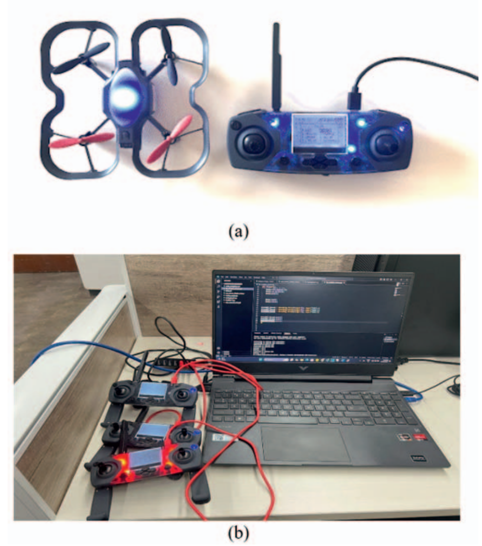

Fig. 6. CoDrone by Robolink: Hardware Setup (By Robolink) Utilised for the deployment of our RSSI localisation Units

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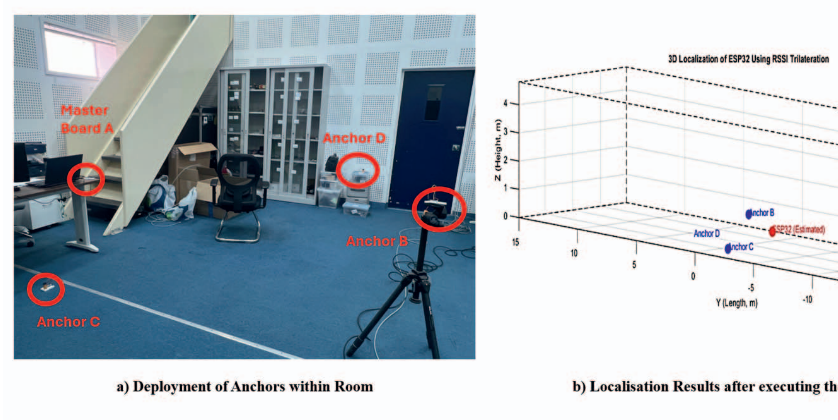

Fig. 7. Localisation using Arduino Nano small units based on the REWL technique.

TABLE IV

Combined Path-Loss Parameters and Localisation Accuracy/Stability Metrics

Method	RSSI_{d_0} (dBm)	β	R^2	RMSE (m)	MAE (m)	Std. Dev. σ (m)	Improvement over WCL
Min–Max	–42.860	2.603	0.9487	0.84	0.71	0.22	–
Trilateration	–43.280	3.801	0.9025	0.65	0.58	0.20	–
Weighted Centroid Localisation (WCL)	–44.752	2.954	0.9342	0.50	0.43	0.14	–
REWL (Proposed)	–46.121	2.131	**0.9723**	**0.31**	**0.27**	**0.08**	**≈38↓MSE**

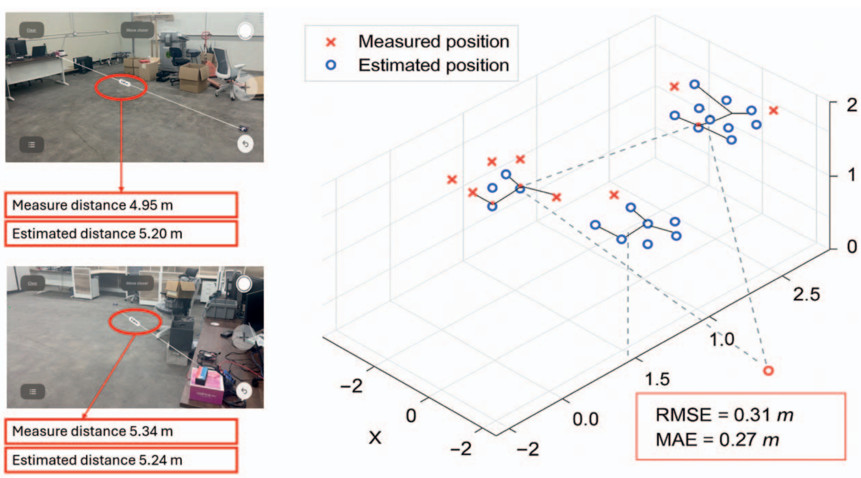

Fig. 8. Deploying the small Arduino Nano-based RSSI localisation Units over CoDrone

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