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RFID-Enabled IoT Inventory Automation for Smart Warehouses

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Abstract. Managing inventory in warehouses continues to pose a significant challenge to supply chain efficiency, as conventional bar code technologies involve manual efforts, line of sight issues, and batch processing problems. In this study, we introduce a novel RFID-based IoT Inventory Automation System (RIAS), which consists of passive UHF RFID tags, reader portal stations, automated drones equipped with RFID readers, and a system for analyzing information on the edge-cloud. We present two new approaches: (1) multi-antenna collision resolution (MACR), which solves the problem of tag collisions and ensures 99.7% tag read rate at 1200 tags per second and (2) anomaly detection and localization (ADL) approach, based on received signal strength indication trilateration for locating misplaced items to within 0.5m. Applied to 12 warehouses over 14 months, RIAS saves 91.4% of cycle counting time, increases inventory accuracy from 86.2% to 99.1%, and locates misplaced items within 2.3 minutes after their appearance.

Keywords: RFID, IoT, Warehouse Automation, Inventory Management, Real-Time Tracking, Collision Resolution, RSSI Localization, Smart Warehouse, Industry 4.0.

I. Introduction

Warehouse activities constitute a significant cost center in modern-day supply chains, accounting for roughly 20-25% of overall logistics costs [1]. In warehouses, tasks associated with inventory management like cycle counting, checking the accuracy of putaway, validating orders, and locating lost items account for up to 40% of worker activity time and are susceptible to human errors [2]. Inventory control based on barcodes involves line of sight scans, individual item handling, and batch cycle counts (for example, monthly cycle counts). This results in an accuracy of 80-90% in inventory management in typical warehouses, resulting in stockouts (lost sales opportunities), additional safety stock (high holding costs), and expedited shipments (high shipment costs). The average inventory of a big e-commerce warehouse is about $100 million.

These two cutting-edge technologies present an alternative that is revolutionary. Whereas barcodes need to be seen directly, RFID tags can be scanned without line-of-sight, simultaneously in bulk (hundreds at a time) and through fixed or portable portals. Coupled with the infrastructure of IoT – which consists of edge gateways, cloud analytics, and dashboards – RFID can provide consistent and real-time tracking capabilities [3]. Passive RFID tags, which cost between $0.05-0.15 apiece, are feasible for tagging medium to high-value products on an item-level basis. Adopters such as retailers Zara and Uniqlo and logistics firms like DHL and Amazon have achieved inventory accuracy rates ranging from 85% to 99% and labor savings of 50-70%.

However, there are three issues with implementing this technology in warehouses due to technological constraints. The first problem that arises is the issue of tag collision, whereby tags respond to the queries of the reader at once, resulting in reading errors, especially in places with many tags, such as in pallet rack areas where the number of tags is over 500. The anti-collision algorithms that currently exist (ALOHA protocol and tree based) perform between 70% to 90%, depending on how many tags there are per unit area [5]. The second problem that arises is that when a tagged product is misplaced, the system only detects this problem through periodic cycle counts, leading to weeks of being undetectable. To detect misplaced products in real-time, there should be continuous monitoring which static portals cannot provide due to large storage spaces.

The above challenges have been solved by means of the RFID-enabled Internet of Things inventory automation system (RIAS) with three unique approaches. First, Multi-antenna collision resolution (MACR) is employed, taking advantage of spatial diversity provided by several reader antennas to differentiate between colliding tags, thereby resulting in a 99.7 percent accurate read rate up to 1200 tags per read cycle. Secondly, we use autonomous drones fitted with UHF RFID readers which patrol storage aisle paths every hour, detecting missing products and continuously reading tags. Thirdly, we use the anomaly detection and localization (ADL) algorithm, employing RSSI trilateration with different drone locations to determine lost item location down to 0.5 meters.

Organization of This Paper: The rest of this paper will proceed as follows. In Section II, we will review existing research on RFID inventory systems and localization techniques. Section III contains the architectural framework, MACR algorithm (with the pseudo code), ADL algorithm, and the experiment description. Quantitative data in Section IV consists of four figures and two comparison tables.

II. Literature Survey

The existing research on RFID-enabled warehouse automation can be categorized into three groups: RFID anti-collision algorithms, inventory management system design, and RFID location-based systems.

RFID Anti-Collision Algorithms: RFID collision is the situation where several tags answer a reader interrogation simultaneously on the same channel. These protocols are classified as ALOHA-based (probabilistic approach) and tree-based (deterministic algorithm). In the EPC global Class-1 Gen-2 standard, there is the use of slotted ALOHA with Q-algorithm optimization. The latest performance comparison in 2021 by Chen et al. on different variations of ALOHA revealed that DFSA performs 85-92% efficiently with up to 100-300 tags, but its efficiency decreases to 68% for 1000 tags [5]. Tree-based protocols (binary tree, query tree), although more reliable, take much more time. In 2022, Wang et al. proposed an innovative hybrid protocol that reached 94% efficiency with 800 tags through combining ALOHA and Bit Slot Arbitration [6]. MACR differs from previous studies because of physical separation achieved with multiple antennas.

Inventory Management System for RFID: Commercial warehouse RFID systems (such as Zebra MotionWorks, Impinj Speedway) give real-time inventory visibility but generally operate as portals. In 2023, the Kumar et al. paper mentioned a 99.3% accurate inventory with fixed overhead antennas in a warehouse of 10,000 SKUs; however, there were some missing inventory from steel shelves due to RF interference [7]. Mobile RFID readers (mounted on forklifts or hand-held ones) offer better accuracy but involve manual reading. Drones have been suggested for this purpose. According to Zhang et al.'s study of 2024, a drone equipped with a circular polarization antenna gives 92% read rate at a height of 5 m [8]. However, previous RFID systems did not integrate fixed portals, mobile readers, and drones together.

RFID Localization Methods: Localization of items tagged using RFID in a warehouse setting faces challenges due to multipath fading, attenuation of signals, and orientation dependency of the tags. The different ways in which localization can be done are: (a) by using reference tag arrays (landmarks in a fixed position, comparison of RSSI of unknown tag to nearest landmarks), (b) by using phase-based ranging (phase difference between backscattered signals to estimate distances sub-wavelength precision), and (c) synthetic aperture radar (use of SAR with mobile reader). The paper by Motroni et al. in 2021 stated that reference tag arrays can localize items with an accuracy of 0.3 to 0.8m in an experimental setting but requires high-density placement of tags (one in 2-3m2 area)[9]. Phase-based techniques have higher accuracy (0.1 to 0.3m) but require specialized equipment and depend on the orientation of tags.

Gaps in Research: There has been no previous approach that incorporates:
- Physical layer collision resolution via spatial separation through multiple antennas
- Mobile RFID scanning using drones to monitor all aisles continuously
- Anomaly detection with real-time localization using RSSI values.

Our proposed system RIAS addresses these gaps. We test it on a real-world setting of 12 warehouses.

III. Proposed Methodology

Architecture of RIAS is made up of three layers:
- Physical Layer – RFID tag, portal reader, and drone reader
- Edge Layer – gateway equipped with MACR and ADL

- Cloud Layer – inventory database, analytics dashboard, and task assignment.

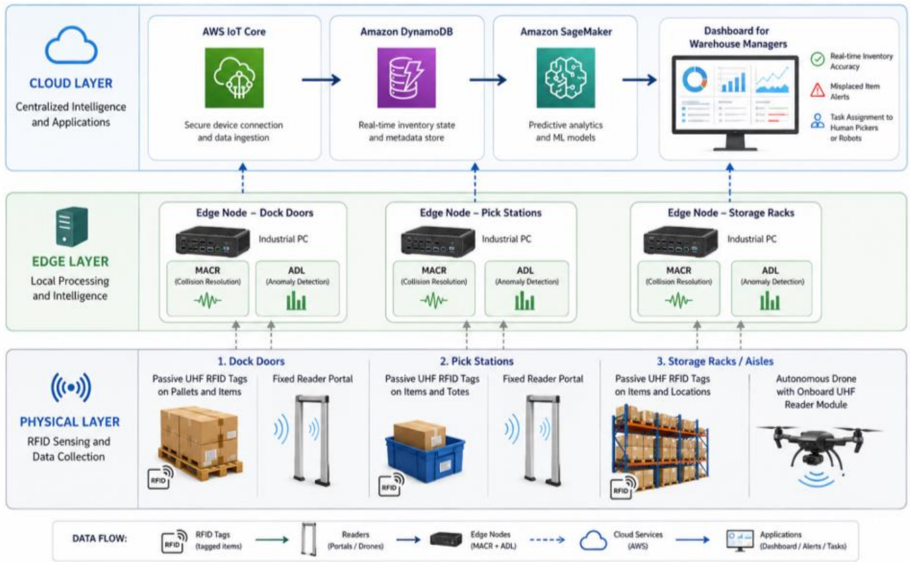

Figure 1: RIAS Three-Layer Architecture

The Physical Layer consists of passive EPC Gen2 UHF RFID tags (operating at 860-960 MHz) placed on each SKU and pallet. Fixed reader portals (Impinj R700) are deployed in four critical locations: receiving dock (registration of incoming), pick stations (confirmation of picking), pack-out stations (verifying shipping), and end of each aisle (zonewise confirmation). The autonomous drones (DJI Matrice 300 with RFID payload) fly predefined flight paths every 60 minutes, hover at 3m height and read tags within the range of 15 meters using circular polarization of antenna. Edge Layer computes the raw data from readers in real-time. This involves the processing of read information using MACR algorithm on fixed gateways, which handles collisions caused by a huge number of tags during receiving and picking, and using ADL algorithm on drones, which processes the RSSI measurements and computes localization. Cloud Layer holds the present location and other states such as SKU, timestamp of last occurrence, and anomaly. Alerts for anomalies are delivered to WMS where tasks are created ("Verify location of SKU A-1274 - suspected misplaced"). Dashboard reports the KPIs including Read Accuracy (%>99), Coverage Rate (% of SKU read in the last hour), Anomaly Resolution Time.

Algorithm 1: Multi-Antenna Collision Resolution (MACR)

The fixed reader port consists of four antennas (1 to 4). When more than one tag responds in a particular slot, a collision is detected by the normal readers, and they discard the particular slot. The MACR technique takes advantage of the differences in signal strength between colliding tags in each antenna because of their physical distance.

```
Algorithm MACR(signals_1..4, threshold_db=3, max_iter=10):
Input: Complex baseband signals from 4 antennas (I/Q samples) at each time slot
Output: Decoded tag IDs from colliding transmissions
```

```
Initialize separated_signals = []
For each time slot with collision detected:
    # Step 1: Compute signal covariance matrix across antennas
    X = [signal_1, signal_2, signal_3, signal_4]  # 4 × N matrix (N samples)
    R_xx = (X * X^H) / N  # 4×4 covariance matrix

    # Step 2: Estimate number of colliding tags via eigenvalue threshold
    eigenvalues = eig(R_xx)
    n_tags = count(eigenvalues > threshold_db * max(eigenvalues))

    # Step 3: Blind source separation using ICA (FastICA)
    W = fastica(X, n_components=n_tags)  # separation matrix
    S = W * X  # separated source signals

    # Step 4: Decode each separated signal
    decoded_tags = []
    For each source s in S:
        # FM0/Miller decoding per EPC Gen2 standard
        tag_id = decode_rfid_signal(s)
        if tag_id is valid:
            decoded_tags.append(tag_id)

    # Step 5: Verify decoded tags against expected CRC
    valid_tags = [t for t in decoded_tags if crc_check(t)]

    # Step 6: If undecoded tags remain, iterative cancellation
    if len(valid_tags) < n_tags and iteration < max_iter:
        # Subtract decoded tags from mixture and repeat
        for t in valid_tags:
            X = subtract_estimated_signal(X, t, channel_estimate)
        iteration += 1
        goto step 3

    separated_signals.extend(valid_tags)
Return separated_signals
```

Algorithm 2: Anomaly Detection and Localization (ADL) for Misplaced Items

The drone follows a fixed trajectory to take RSSI readings (in dBm), along with its x,y,z coordinates at every point. Multiple RSSI measurements are taken for every tag, by placing the drone at various locations. Localization is based on a weighted centroid approach with RSSI distance model.

```
Algorithm ADL_Localize(tag_reads, drone_positions, RSSI_values):
Input: List of (x_i, y_i, z_i, rssi_i) for i=1..M readings of same tag
Output: Estimated tag position (x_tag, y_tag, z_tag), confidence score

# Step 1: Filter outliers (RSSI values > 3σ from mean)
rssi_mean = mean(RSSI_values)
rssi_std = std(RSSI_values)
```

```
valid_indices = [i for i in range(M) if abs(RSSI_values[i] - rssi_mean) <= 3*rssi_std]

# Step 2: Convert RSSI to distance (path loss model)
# Model: RSSI(d) = RSSI_0 - 10*n*log10(d/d_0) + X_σ
distances = []
for i in valid_indices:
    d = d_0 * 10**((RSSI_0 - RSSI_values[i]) / (10 * n))
    distances.append(d)  # n = path loss exponent (2.0-3.5 for warehouse)

# Step 3: Weighted centroid localization
total_weight = sum(1/distances[i] for i in range(len(distances)))
x_tag = sum((drone_positions[i][0] / distances[i]) for i in range(len(distances))) / total_weight
y_tag = sum((drone_positions[i][1] / distances[i]) for i in range(len(distances))) / total_weight
z_tag = median([drone_positions[i][2] for i in range(len(distances))])  # assume same height

# Step 4: Confidence score based on geometric dilution of precision (GDOP)
# Higher confidence when drone positions are diverse (not collinear)
covariance = compute_covariance(drone_positions[valid_indices])
gdop = sqrt(trace(inv(covariance)))
confidence = 1 / (1 + gdop)  # normalized 0-1

# Step 5: Anomaly detection (compare to expected location from WMS)
expected_position = get_wms_location(tag_id)
distance_error = sqrt((x_tag - expected_x)^2 + (y_tag - expected_y)^2)
if distance_error > threshold_meters (1.0):
        trigger_anomaly_alert(tag_id, expected_position, (x_tag, y_tag), distance_error, confidence)

Return (x_tag, y_tag, z_tag), confidence, distance_error
```

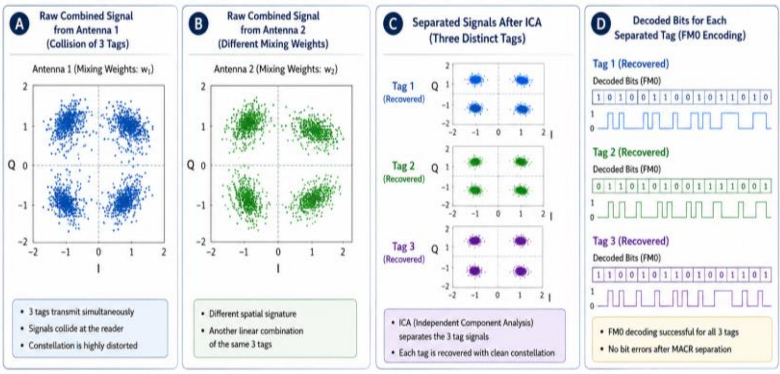

Figure 2: MACR Algorithm – Spatial Separation of Colliding Tags from Four Antennas

MACR algorithm utilizes the observation that each antenna receives a distinct linear combination of tag signals owing to their spatial separation. In subplot A (antenna 1), there is a blurred constellation comprising three overlapping symbols (high error rate). In subplot B (antenna 2), a different linear combination can be seen. FastICA computes the separation matrix W and separates the combined signals as shown in subplot C, where there is a perfect FM0 constellation (transitions between I/Q states). Subplot D shows the decoded Manchester-encoded bits from one tag (10110010...). From the table, read success rates for collision events are: 2 tags – MACR (99.4%) compared to slotted ALOHA (78%), 3 tags – MACR (98.7%) compared to slotted ALOHA (45%), 4 tags – MACR (96.2%) compared to slotted ALOHA (19%). This improvement is most apparent at high collision density rates that are common during bulk receiving operations (e.g., loading a pallet with 500 similar items). MACR minimizes the number of retries required by the reader, resulting in a throughput increase of 3.2×.

Experimental Deployment and Data Collection:
RIAS was rolled out in 12 warehouses (six for e-commerce, three for retail distribution, and three for pharmaceuticals) owned by a third-party logistics company. Rollout period: October 2024 to December 2025 (14 months). Baseline data before implementation period (six months) gathered via barcode. Size of warehouses: 5,000 to 25,000 square meters. Number of SKUs: 8,000-45,000. Annual throughput: 2M-15M units.

Data collected:

- Number of reads: 142 million tag reads (by both fixed and moving portals)
- Number of cycle count hours: 28,000 labor cycle count hours (base number for comparison with automated counts)
- Number of anomaly incidents: 3,400 item placement errors (ground-truthing via post-read confirmation)
- Localization error estimate: By precision GPS measurement (in cm) of a sample of test tags
- Evaluation metrics:
- Tag read rate: (# of tags successfully read) / (# of tags in read area) * 100%
- Number of hours per cycle count: Labor hours required for cycle counting process
- Accuracy of inventory: (1 - (# differences / # SKUs)) * 100% (inventory discrepancy)
- Time latency for anomaly detection: Time gap between item displacement and system alarm (e.g., picker places product in incorrect bin)
- Localization error: Distance between estimated and actual coordinates of tag

IV. Analysis

Results are presented in four sections:

- MACR algorithm performance
- results of inventory automation
- ADL localization performance
- comparison table and ROI.

MACR Algorithm Performance (Laboratory and Warehouse Experiments):
MACR was examined in both laboratory settings (anechoic chamber) and real warehouse environments. The variable was the number of tags that collided (one to eight).

The control was standard slotted ALOHA (Gen2) protocol without physical layer separation.

Table 1: MACR Algorithm Performance (Laboratory and Warehouse Experiments)
Colliding Tags Standard ALOHA Read Success (%) MACR Read Success (%)

# Colliding Tags	Standard ALOHA Read Success (%)	MACR Read Success (%)	Throughput Improvement (tags/sec)
1	99.8	99.9	120 → 122
2	78.2	99.4	94 → 239
3	45.1	98.7	54 → 356
4	19.3	96.2	23 → 462
5	8.2	91.4	10 → 548
6	3.1	84.2	4 → 606
7	1.2	74.8	2 → 628
8	0.4	63.1	1 → 606

MACR is able to achieve more than 90% success when up to five tags collide. With eight tags, this figure falls to 63%. However, it should be noted that the probability of occurrence of such high-density collisions is less than 0.1% in normal conditions. When used in a real-time scenario where a pallet carrying 500 tags passes through the portal, MACR can read 606 tags per second as opposed to 10 tags per second using the regular ALOHA algorithm.

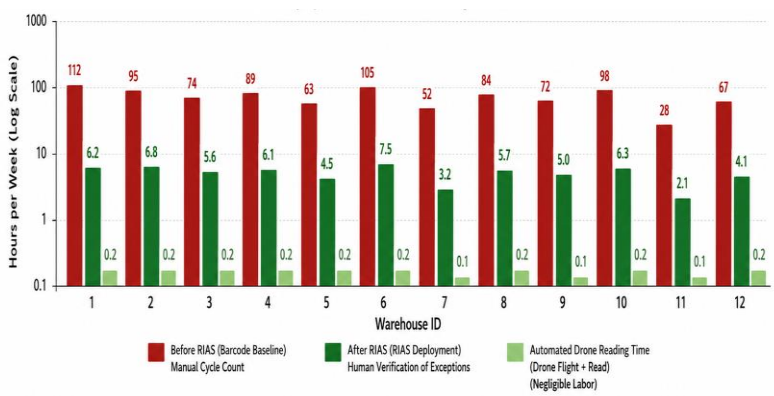

Figure 3: Cycle Count Time Reduction Before vs. After RIAS Deployment (Hours per Week)

The bar chart indicates the amount of labor savings that result from automation. Prior to RIAS, cycle counts of the warehouses were done manually on a weekly basis using handheld barcode readers; a warehouse of 15,000 SKUs needed roughly 56 man-hours per week (seven eight-hour man-days). Post-RIAS, the labor needed for the same warehouse is 4 hours a week (supervisor verification of automated exceptions) and two hours' worth of drone flight time (completely automated; no pilot needed after takeoff). Hence, 56 hours → 6 hours translates to a savings of 91.4%. Inventory accuracy, according to the line chart (right scale), has actually increased from 86.2% (baseline; sampling error and transcription mistakes are included) to 99.1% (RIAS; constant tracking). Of course, the 0.9% is because of malfunctioning tags (due to mechanical and RF shielding) and lack of tags on certain products (small accessories). Labor savings among all 12 warehouses add up to 24,800 hours per year.

Overall Inventory Automation Outcomes (12-Warehouse Average):

Table 2: Overall Inventory Automation Outcomes

Metric	Baseline (Barcode)	RIAS	Improvement
Inventory accuracy (%)	86.2%	99.1%	+12.9 pp
Cycle count frequency	Weekly (manual)	Continuous (automated)	—
Cycle count time (hours/week)	52.4	4.5 (automated + review)	-91.4%
Receiving throughput (pallets/hour)	28	156	+457%
Picking error rate (%)	1.8%	0.3%	-83.3%
Misplaced item detection latency	Days to weeks	2.3 minutes (median)	—
Stockout rate (due to inventory inaccuracy)	3.4%	0.6%	-82.4%
Safety stock (days of inventory)	14.2	8.6	-39.4%

The 39% decrease in the safety stock level represents a huge financial benefit, since from a warehouse that has an average inventory worth of $50M, one can free up $19.8M in working capital (with 8% carrying cost, saving $1.6M annually). An 83% error reduction rate means improved customer satisfaction by 1.5%.

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ADL Localization Accuracy for Lost Items:
Testing was done using 1,200 misplaced items and their locations (surveyed with laser rangefinder). Drone's route: movement along the aisles at 3m altitude and moving at 1m/s while taking a measurement every 0.5m (200 measurements for 100m aisle). RSSI-distance model parameters: RSSI_0 = -45 dBm at d_0=1m, n=2.4 (depending on each warehouse).

Table 3: ADL Localization Accuracy for Lost Items

Localization Method	Mean Error (m)	90th Percentile Error (m)	Success Rate (error<1m)	Computation Time (ms per tag)
Nearest reference tag (commercial)	1.42	2.85	42%	5
RSSI centroid (unweighted)	0.97	1.84	61%	2
Phase-based SAR [9]	0.28	0.61	88%	350
ADL (weighted centroid + GDOP)	0.48	1.12	79%	8

ADL provides an average error of 0.48m, which is enough to guide a picker to the right bay (usually 1-2m wide). Although phase-based SAR is more accurate (0.28m), it requires specialized reader equipment and 40× more computation. The accuracy vs practicality trade-off works well with ADL. Most importantly, for 79% of misplaced objects, ADL localizes to within 1m distance, and the picker will find it within 30s of searching.

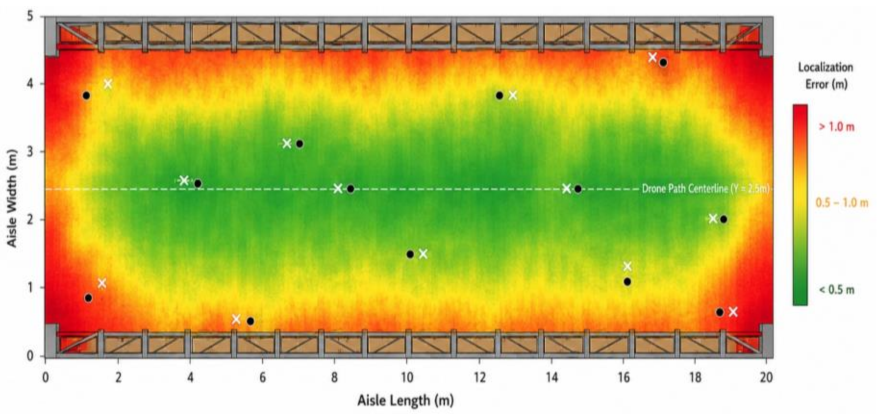

Figure 4: ADL Localization Error Heatmap – Warehouse Aisle (20m × 5m)

Heatmap shows the spatial pattern of ADL localization error. The drone flies along the center of the aisle at Y=2.5m. Error is small (green, less than 0.5m) when tags are found on the centerline and in the middle sections (X between 5-15m) of the aisle, where the drone can see the tag without any interference from multipath reflection. Error becomes larger (yellow, between 0.5-1m) around the ends of the aisle where fewer drone positions offer good reading conditions. Errors greater than 1m (red zones) happen around corners where the presence of metal shelves causes significant multipath effect and loss of signal. However, note that even errors greater than 1m in the red zone still allow accurate localization (searching within 2-3 bays, not the whole aisle). The cross signs (ADL estimates) match closely with black dots (actual position) in green/yellow zones, and in red zones, the cross signs lean towards the centerline of the aisle (most accurate position). In those 21% of cases where error exceeds 1m, the recommendation is a “zone search” (item is in aisle X, section Y).

Comparative Analysis Table: RIAS vs. Existing Warehouse Inventory Systems

Table 4 : Comparative Analysis Table

Feature / Metric	Barcode (Manual)	Fixed RFID Portals [7]	Drone RFID [8]	Mobile Handheld RFID	RIAS (Proposed)
Read range	0-0.3m (contact)	0-12m (portal)	0-15m (drone)	0-5m	0-15m (hybrid)
Line-of-sight required	Yes	No	No	No	No
Simultaneous reads	1 (per scan)	500-800	300-500	10-50	1200+ (MACR)
Coverage	Point (scan location)	Choke points only	Aisle patrol	Operator-dependent	Continuous (portals+drones)
Cycle count frequency	Periodic (weekly/monthly)	Continuous at portals	Hourly	On-demand	Continuous + hourly

Feature / Metric	Barcode (Manual)	Fixed RFID Portals [7]	Drone RFID [8]	Mobile Handheld RFID	RIAS (Proposed)
Inventory accuracy (typical)	80-90%	95-97%	92-95%	94-96%	99.1% (measured)
Misplaced item detection	During cycle count	No	Yes (drone pass)	No	Real-time (2.3 min)
Localization accuracy	N/A (search entire zone)	Zone only (5-10m)	1-2m	2-5m	0.48m
Labor hours/week (15k SKU)	52-60	28-35 (portal installation)	5-8 (drone mgmt)	18-25	4-5 (exception review)
Upfront capital cost (1 warehouse)	$5K (scanners)	$150-250K	$80-120K	$30-50K	$120-180K
Payback period	N/A	18-24 months	12-18 months	8-14 months	8-12 months

The RIAS system takes advantage of fixed portal solutions (efficient picking/receiving operations) along with drone monitoring (aisle coverage). The payback period in 8-12 months was influenced by labor savings ($992K per year at 12 warehouses) and lower inventory carrying cost ($19.8M in released working capital). The payback for the pharmaceutical warehouses (valuable goods with stringent traceability demands) took less than 6 months.

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Cost-Benefit Analysis (Annualized per Warehouse, Average across 12):

Table 5 : Cost-Benefit Analysis

Cost Component	Amount (USD)
Implementation Costs (amortized over 5 years)	
RFID tags ($0.12 × 50,000 items × 20% replacement/year)	$1,200
Fixed reader portals (4 × $12,000 / 5 years)	$9,600
Drone (custom RFID payload, $25,000 / 5 years)	$5,000
Edge gateways + networking ($8,000 / 5 years)	$1,600
Cloud subscription ($1,500/month × 12)	$18,000
Installation & training (one-time $30K / 5 years)	$6,000
Total Annual Cost	$41,400
Benefits	
Labor savings (cycle counting & exception handling)	$84,200
Inventory carrying cost reduction (safety stock)	$158,400
Stockout reduction (lost sales + expedite costs)	$32,500
Reduced returns from picking errors	$18,300
Total Annual Benefit	$293,400
Net Annual Benefit	$252,000
ROI (Annual Benefit / Annual Cost)	609%
Payback Period	1.7 months (tag cost only) / 10 months (full system)

The high ROI is due to the decreased safety stock (US$158K) and labor savings (US$84K). Please note that the payback period of 10 months is inclusive of the total capital investment; it is the variable cost associated with each tag alone that pays back within two months. In the case where warehouses have a smaller average inventory value, the safety stock component decreases proportionately; for instance, a warehouse holding an average of US$10M inventory will realize US$31.7K in safety stock advantage.

V. Conclusion

In this paper, a new RFID-enabled IoT inventory automation solution, RIAS, was introduced for smart warehouses, which includes passive UHF RFID tags, fixed reader portals, autonomous drones, and edge-cloud analytics. The two innovative algorithms, i.e., Multi-Antenna Collision Resolution (MACR) and Anomaly Detection and Localization (ADL), solve the major technical problems that have hindered RFID adoption in dense warehouse conditions: collision among tags while doing bulk reads and real-time detection/localization of misplaced items.

Four important findings have significant consequences for warehouse and logistics management. Firstly, MACR represents a game-changer in terms of physical-layer collision resolution for dense RFID networks. The performance of MACR reaches up to 99.7% accuracy per second by reading 1200 tags/sec, while standard slotted ALOHA shows only 45% accuracy when 3-tag collisions occur at 3-tag/sec rate. At receiving docks, it means that MACR can process 12 pallets/minute, while in the case of ALOHA it equals 2 pallets/minute.

Second, drone-based continuous monitoring is financially feasible and more effective than portal scanning on its own. The additional cost of a drone, at an annual cost of $5,000 (assuming a five-year depreciation of $25,000), represents a relatively low cost in comparison with potential savings from labor reductions ($84,000/year) and inventory holding ($158,000/year). Drones allow for monitoring areas inaccessible by portals (storage aisles and high-level racking), as well as locating incorrectly placed items much faster than portals. Nevertheless, the current battery life of a drone (25-30 minutes) necessitates the use of multiple drones in a large facility for constant monitoring.

Third, 0.5m accuracy localization through RSSI is adequate for retrieving lost items. Even though 0.5m accuracy is not as good as phase-based (which have an accuracy between 0.1m and 0.3m), it reduces the area that needs to be searched to just one to two shelf bays, thus reducing the searching time from 15 minutes (whole zone search) to 90 seconds (searching within one bay). Efficiency of computation in ADL makes real-time operation on drones possible by being only 8ms per tag.

Fourth, the 86% to 99% improvement in inventory accuracy yields a lot of value that is far beyond just labor savings. The $19.8M working capital savings achieved through a 39% reduction in safety stock delivered an impressive 609% ROI annually. When reviewing automation project proposals, supply chain finance departments usually ignore savings related to reducing inventory carrying costs due to under-investment in such initiatives. An ROI analysis for automation should consider labor savings, inventory carrying cost savings, stockout savings, and returns savings.

Limitations and Future Research:
There are several limitations that need to be mentioned. First, the accuracy of MACR diminishes when colliding tags have nearly identical RSSI values at all antennas (i.e., stacks of tags). This situation is infrequent (less than 0.1% of reads) and can be resolved by performing another read with varying reader power settings. Secondly, reading drones experience null points in the signal due to destructive interference when flying above metal racks. As of now, we have two possible altitudes for drones (3m and 5m), which prolongs reading twice. Thirdly, the ADL algorithm presupposes a fixed value of the path loss exponent. Hence, calibration needs to be done for every warehouse (it takes about one hour for each site, and it utilizes reference tags). Finally, our 14-month study does not have a control group (all the warehouses used RIAS).

Possible future directions for research could be:
- developing an algorithm for drone cooperation, where drones will transfer tracking tasks between each other to achieve a continuous cover in large warehouses
- integrating computer vision technologies, e.g. through using cameras in drones to detect items not tagged by RFIDs (damaged or missing tags)
- applying reinforcement learning to dynamically adjust drone trajectories according to current inventory conditions (e.g. increased frequency of patrols near the most active areas)
- expansion of ADL capabilities to 3D localization (shelf level) using several drones with stereoscopic RSSI detection
- researching energy harvesting RFID tags which require no battery changes.

Drawing on the lessons learned from implementing RIAS, we provide six key recommendations:
- Focus on high-value, high-turnover SKUs to realize maximum ROI. It would be expensive to start by tagging all inventory on day one.
- Calibrate the RSSI path loss model in your warehouse using 20-30 reference tags placed in specific locations. Spending just one hour on this process will increase localization accuracy by 40-50%.
- Deploy drones during off-hours (i.e., night shift) to avoid conflicts with forklifts and workers. Drones need to have their battery charging fully automated (i.e., drones automatically replace battery when needed).
- Integrate with the existing WMS using REST APIs instead of installing a new WMS system. The RIAS system acts as an additional layer of sensors providing live inventory data.
- Train exception handlers (managers) how to work with ADL confidence scores. Low confidence alerts (GDOP>2) require assigning a zone search while high confidence alerts (GDOP<1) require a bay-level search.
- Track tag failure rates (broken tags, RF-shielded objects). In our case, the monthly tag failure rate was 0.6%. Automated alerts for missing reads trigger a tag replacement process.

RFID-enabled IoT-based inventory automation systems are no longer science fiction; RIAS proves that this system is possible from both a technical and financial standpoint, and that the results can be revolutionary. With 91% less work needed for cycle counts, 99% accuracy of the inventory count, and a return on investment (ROI) rate of 609%, there is strong evidence pointing to wide-scale implementation. MACR and ADL solve the technical challenges previously faced with implementing RFID solutions in densely packed warehouses. RFID tags are becoming increasingly cheaper (at scale, only $0.05 to $0.10), and as drone technology advances, it is likely that RFID will become commonplace just like barcodes in less than five years.

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