International Journal of Technology 17(4) 1413-1431 (2026)

International Journal of Technology

http://ijtech.eng.ui.ac.id

Research Article

Integrated Unmanned Aerial Vehicles (UAV) Swarm Architecture for Wireless Communication and Drone Logistics in Global Navigation Satellite System-Denied Smart Warehouses

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Abstract: Reliable wireless communication remains a major challenge in indoor transportation environments. Signal attenuation, multipath propagation, and dynamic obstacles significantly degrade communication reliability in logistics warehouses and automated industrial facilities. Conventional Distributed Antenna Systems (DAS) enhance coverage but are limited by their statically deployed nature. Recent research has proposed that unmanned aerial vehicles (UAVs) can be used as mobile relay nodes for wireless link connections in complex environments. This study proposes a hybrid communication architecture of Distributed Antenna Systems and UAV-Assisted Relays and Machine Learning based optimization technique for indoor transportation and warehouse environments to enhance wireless coverage and reliability. The proposed framework combines a DAS infrastructure with autonomous UAV relay nodes. An indoor propagation model is used to assess the signal behavior, and a machine learning-based optimization algorithm is used to determine the optimal UAV positioning to maximize signal quality and minimize communication latency. Simulation results show that the UAV-assisted DAS architecture improves coverage probability and average signal quality compared to conventional DAS deployments, and communication latency is reduced for dynamic indoor scenarios. The proposed hybrid system offers an adaptive solution for indoor transport communication networks to enhance the reliability and scalability of smart warehouses and automated logistics systems. Additionally, based on the proposed architecture, UAV platforms can be used to complete aerial logistics tasks, including inventory verification, cargo delivery between warehouse areas, and real-time infrastructure surveillance, thus changing the communication relay network into a multipurpose aerial logistics support platform.

Keywords: Distributed antenna system; Indoor wireless communication; Reinforcement learning; UAV swarm networks; Warehouse automation

1. Introduction

Unmanned aerial vehicles (UAVs) have found a broad range of applications in wireless communication, sensing, and logistics because of their flexibility and quick deployment capabilities. In particular, UAV-assisted communication systems have shown dramatic enhancements in coverage and reliability in complex environments with reported enhancement of up to 20–60% in signal coverage (Fotouhi et al., 2019; Gupta et al., 2015; Zeng et al., 2016; Zhang et al., 2019). Compared with single-UAV systems, swarm-based architectures offer greater scalability, redun-

https://doi.org/10.14716/ijtech.v17i4.8474
Received March 2026; Revised April 2026; Accepted June 2026

dancy, and spatial coverage, which can deliver robust operations in dynamic and large-scale environments, such as industrial facilities and logistics infrastructures (Bekmezci et al., 2013; Chung et al., 2018; Jawhar et al., 2017).

Despite these advantages, most existing UAV communication frameworks rely on Global Navigation Satellite Systems (GNSS) for localization and coordination. However, GNSS signals are often unavailable or unreliable in indoor environments, such as warehouses and underground and dense industrial environments. These GNSS-denied conditions seriously affect the navigation and coordination performance of UAVs, making communication and control more challenging.

Distributed antenna systems (DAS) have been extensively implemented to overcome these shortcomings and improve wireless coverage within large indoor settings. DAS can reduce propagation loss and improve signal availability by deploying several antenna nodes over the service area (Andrews et al., 2014; Saleh et al., 2003). However, fixed DAS deployments have an inherent limitation for adapting to dynamic propagation situations and commonly experience coverage gaps due to obstacles, shadowing, and multipath effects in complex indoor environments (Goldsmith, 2005; Hashemi, 2002; Molisch, 2012; Rappaport, 2002).

The use of UAVs as mobile relay nodes to complement static communication infrastructures has been studied in recent research. A UAV-assisted relay network can dynamically adjust the position to reduce signal degradation and enhance network connectivity. Progress in artificial intelligence and reinforcement learning (RL) has enabled the development of adaptive control strategies for UAV navigation and positioning in complicated environments. Learning-based approaches enable UAV agents to be optimized for their trajectories and communication performance based on their interaction with the environment (Huang et al., 2019; Lahmeri et al., 2021; Lv et al., 2023; Wang et al., 2022).

In addition to communication support, UAV platforms are increasingly used in smart-warehouse logistics operations, including inspection, monitoring, lightweight delivery, and inventory verification (Dorling et al., 2016; Goodchild & Toy, 2018; Murray & Chu, 2015). Recent studies have examined UAV communication systems, indoor drone localization, and logistics technology implementation (Firmansyah et al., 2025; Pyykkö et al., 2024; Shafik et al., 2024). However, these studies do not jointly address adaptive indoor wireless coverage and UAV-based logistics execution in GNSS-denied smart warehouses.

Therefore, the novelty of this study lies in a joint cyber-physical architecture in which UAVs operate simultaneously as adaptive wireless relay nodes and aerial logistics agents. The proposed framework integrates fixed DAS coverage, UAV-based multi-hop relaying, DQN-based adaptive positioning, and logistics-task execution within a single simulation model.

The major contributions of this work are summarized as follows:

(1) A hybrid GNSS-denied smart warehouse communication architecture is proposed, which integrates a fixed distributed antenna system (DAS) with an adaptive UAV swarm relay layer. Unlike conventional static DAS deployments, the proposed architecture enables UAV agents to dynamically compensate for local coverage gaps caused by racks, obstacles, and multipath shadowing.

(2) A joint communication–logistics cyber-physical model is developed in which UAV platforms are represented as multifunctional agents capable of supporting wireless relaying, inventory inspection, lightweight item transport, and warehouse monitoring within the same operational framework.

(3) A multi-objective optimization formulation is introduced to balance communication quality, coverage probability, logistics workload completion, UAV energy consumption, communication delay, and relay-topology connectivity. This objective explicitly links the reliability of wireless communication with warehouse logistics performance.

(4) A reinforcement-learning-based UAV positioning strategy is designed to adaptively determine UAV movement decisions based on real-time signal quality, residual energy,

relay connectivity, and logistics task status.

(5) A simulation-based evaluation was performed in a GNSS-denied warehouse environment with obstacle-induced attenuation, multipath propagation, DAS coverage, UAV relay deployment, and logistics task execution. The proposed framework is compared with conventional DAS-only and non-adaptive UAV relay baselines to demonstrate its communication and operational benefits.

This integrated approach can offer a scalable and adaptive solution to improve the reliability and operational efficiency of communication in next-generation smart warehouse systems.

2. Methods

2.1 Proposed UAV-Assisted DAS Framework System

The proposed framework integrates a distributed antenna system (DAS) with an unmanned aerial vehicle (UAV) swarm relay layer to provide reliable communication in indoor environments. The system has three layers: (i) DAS infrastructure, (ii) UAV relay swarm, and (iii) ground nodes. Figure 1 shows the hybrid architecture for the proposed system, where the distributed antenna infrastructure is responsible for the major wireless coverage and the UAV relay nodes dynamically optimize their positions to enhance the wireless connectivity within the shadowed areas.

Figure 1 shows that the DAS layer provides baseline indoor wireless coverage, whereas the UAV swarm forms an adaptive relay layer that dynamically compensates for local shadowing and coverage gaps. The detailed relay topology in Figure 1(b) also clarifies how neighboring UAVs cooperate through multi-hop links to preserve connectivity between fixed infrastructure and ground nodes with limited communication.

The communication network can be modeled as a dynamic graph as follows:

$$G(t) = (V, E(t)) \tag{1}$$

where V denotes the set of network nodes, including distributed antennas, UAV relays, and ground communication devices, and $E(t)$ denotes the time-dependent communication links between nodes.

2.2 Indoor Radio Propagation Model

Accurate indoor radio propagation modeling is required to evaluate the proposed UAV swarm-assisted DAS system and determine relay deployment strategies. Indoor wireless performance is affected by distance-dependent attenuation, multipath propagation, and obstacle-induced shadowing. Therefore, classical path-loss and multipath models are used as the basis for signal analysis in the warehouse environment (Goldsmith, 2005; Hashemi, 2002; Molisch, 2012; Rappaport, 2002).

Indoor signal propagation is also affected by reflections from walls, floors, ceilings, and metallic surfaces. The received signal power considering multiple propagation paths is expressed as

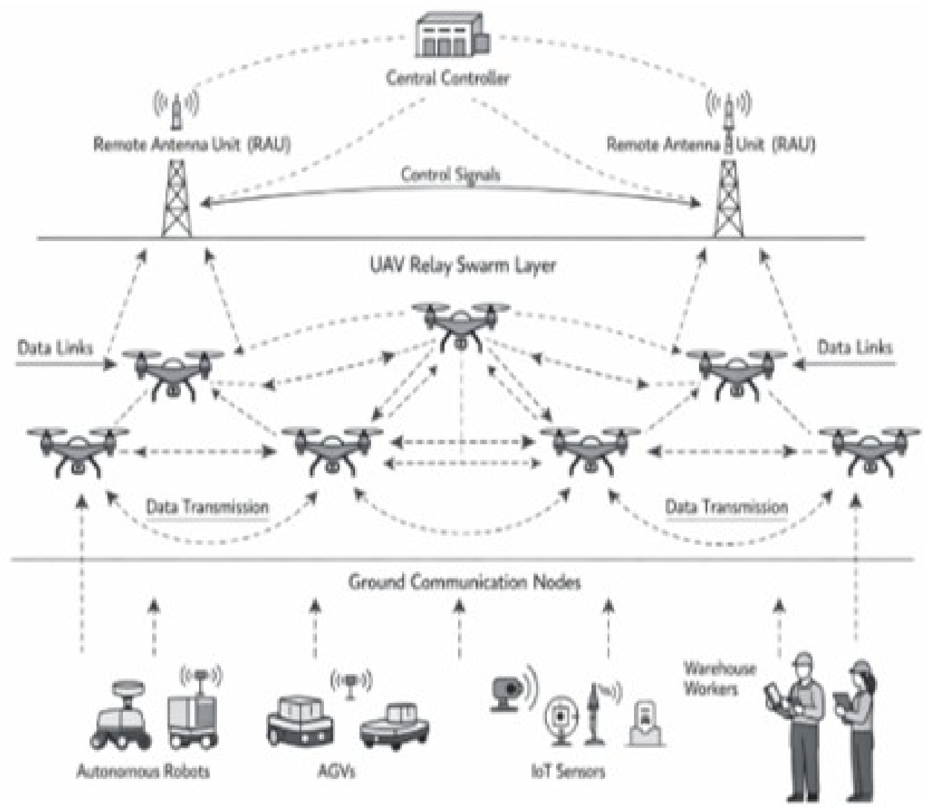
$$P_r = \sum_{i=1}^{N} P_i e^{-j\phi_i} \tag{2}$$

where P_i is the power of the i-th propagation path and ϕ_i is the phase shift incurred by the propagation distance of the i-th propagation path. The combination of multiple signal components causes spatial variations in indoor signal strength.

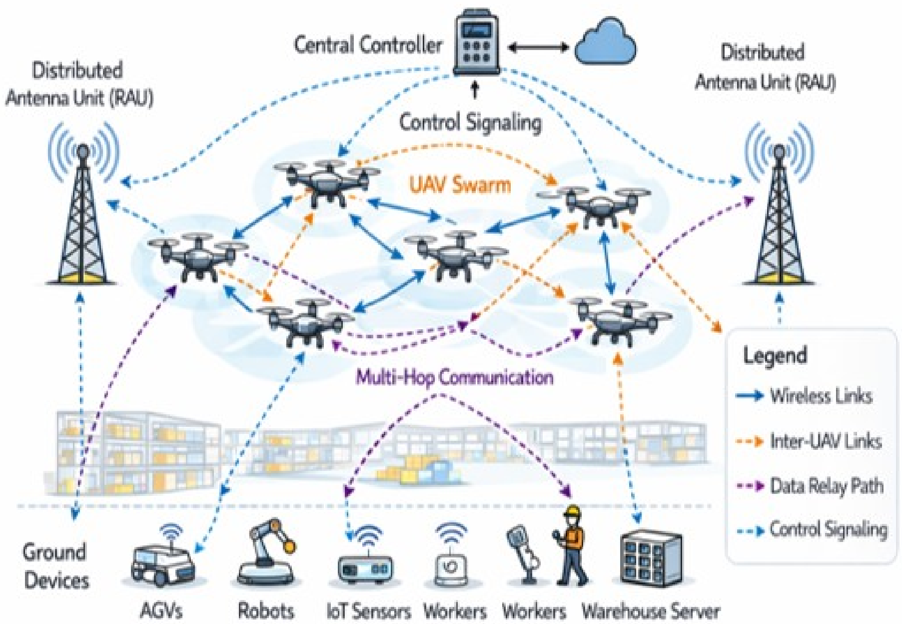
Obstacle-induced attenuation is included as an additional loss term. When the signal passes through an obstacle with thickness, the extra attenuation is given by

$$L_0 = \alpha d_0 \tag{3}$$

where L_0 is the obstacle attenuation and α is the material-specific attenuation coefficient.



(a)



(b)

Figure 1 Proposed hybrid DAS–UAV architecture for GNSS-denied smart warehouses: (a) overall system architecture including the DAS infrastructure, UAV swarm relay layer, and ground nodes; (b) cooperative UAV swarm relay topology enabling adaptive multi-hop communication between DAS antennas and ground devices in shadowed areas

The combined propagation model therefore includes distance-dependent path loss, multipath interference, and obstacle attenuation. This model provides the basis for evaluating signal distribution and UAV relay positioning in GNSS-denied transport facilities.

2.3 Distributed Antenna System Model

The distributed antenna system (DAS) is the backbone of the proposed hybrid architecture because it is a fixed communication system. In the case of large indoor transportation environments (e.g., warehouse, logistics hub, etc.), DAS infrastructure is used to distribute the radio signals using multiple spatially separated antenna units connected to a centralized controller. This configuration is used to minimize the propagation losses compared with a single centralized antenna and improve the signal availability over the facility. Distributed antenna systems (DAS) have been widely used for wireless coverage in large indoor facilities, such as airports, warehouses, and industrial plants. DAS architectures minimize the propagation signal losses and enhance the signal availability of a centralized antenna system by distributing several antenna units throughout the service area. Despite these benefits, fixed DAS deployments may experience coverage gaps caused by obstacles and structural attenuation in complex indoor environments (Andrews et al., 2014; Saleh et al., 2003).

In the proposed system, the DAS has a central baseband processing unit that is connected to some distributed antenna nodes through a wired or optical backhaul connections. These antenna nodes are installed at strategic points in the indoor environment to introduce base-line wireless coverage of ground devices and UAV relay nodes. However, due to structural hindrances and complex indoor geometry, signal distribution using fixed antennas alone can cause coverage gaps and signal strength in areas of low signal strength.

The received signal power to a node a distance d away from the transmitting antenna is modeled as follows:

$$P_r = P_t + G_t + G_r - PL(d) \tag{4}$$

where P_r is the received signal power, P_t is the transmitted power of the antenna, G_t and G_r are the transmitter and receiver antenna gains, respectively, and $PL(d)$ is the path loss given by the indoor propagation model in Section 2.2. The indoor service area is divided into several parts of the service coverage related to the distributed antenna nodes. Every antenna covers a local area in which the power of the received signal is greater than the minimum power P_{th}. Therefore, the coverage probability of the DAS infrastructure is defined as

$$P_{cov} = P\left(P_r \geq P_{th}\right) \tag{5}$$

where P_{cov} is the probability that the received signal strength at a given location is greater than the communication threshold required for reliable data transmission.

The coverage area of each antenna can be approximated using spatial partitioning techniques, such as Voronoi tessellation. In this representation, the closest antenna node is associated with each point inside the environment; thus, the communication coverage area of each antenna can be defined as follows:

$$V_i = \left\{ x \in \mathbb{R}^2 \;\middle|\; \|x - a_i\| \leq \|x - a_j\|,\, \forall j \neq i \right\} \tag{6}$$

where V_i represents the Voronoi region of antenna a_i. Despite the new spatial distribution image that DAS offers, signal attenuation by obstacles may still lead to localized communication failures. These regions are covered by the UAV swarm relay layer, which dynamically adjusts its positions to cover the effective communication range beyond the fixed antenna infrastructure's limitations.

2.4 UAV Swarm Communication and Relay Model

In the proposed system, the UAV swarm is used as a mobile relay network, which is intended to improve the communication coverage in areas where the distributed antenna infrastructure cannot maintain reliable communication. By dynamically altering their location in the indoor environment, UAVs can overcome the effects of signal degradation in terms of structural obstacles, radio shadowing, and multipath propagation.

Each UAV is equipped with a wireless communication module, an onboard processing unit, a navigation subsystem, and an energy-monitoring module. UAV nodes communicate with neighboring UAVs and DAS antennas to form a cooperative multi-hop relay network. In addition to communication relaying, UAVs can also support inventory inspection, lightweight parcel transport, and infrastructure monitoring, making them multifunctional agents in the proposed warehouse architecture (Dorling et al., 2016; Goodchild & Toy, 2018; Murray & Chu, 2015).

The swarm communication topology can be modeled using an adjacency matrix of the connectivity between UAV nodes. A communication link between two UAV nodes i and j is provided if the distance between them is at most the communication radius r_c. Therefore, the connectivity matrix is defined as

$$A_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq r_c \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where d_{ij} is the Euclidean distance between UAV nodes i and j. This connectivity structure allows the formation of a dynamic communication graph, in which UAV nodes work together to ensure connectivity between ground devices and the distributed antenna network.

In the relay communication process, the UAV nodes adopt the decode and forward strategy. In this scheme, an intermediate UAV node receives a signal, decodes the transmitted information, and retransmits the received signal to the next node in the communication path. The received signal power of UAV node i from transmitting node j can be written as follows:

$$P_{r,i} = P_{t,j} + G_{t,j} + G_{r,i} - PL\left(d_{ij}\right) \tag{8}$$

where $P_{t,j}$ is the transmitted power of node j, $G_{t,j}$ and $G_{r,i}$ are the transmitter and receiver antenna gains, and $PL\left(d_{ij}\right)$ is the path loss between the nodes.

Figure 1(b) illustrates the cooperative relay structure of the UAV swarm, where UAV nodes form adaptive multi-hop communication paths between distributed antenna units and ground devices located in shadowed areas.

Energy consumption is a key constraint in UAV swarm communication systems, as UAV flight and communication operations are constrained by the limited battery capacity on board the UAVs. The total energy consumption of UAV node i is modeled as

$$E_i = E_{prop,i} + E_{comm,i} + E_{proc,i} \tag{9}$$

where $E_{prop,i}$ is the propulsion energy needed for flight, $E_{comm,i}$ is the energy for communication (wireless transmission and reception) and $E_{proc,i}$ is the energy for the onboard processing tasks.

To mathematically represent the logistics operations in the warehouse environment, let the set of logistics tasks be defined as

$$T = \{T_1, T_2, \ldots, T_M\} \tag{10}$$

where T_k represents the k-th logistics task, M is the total number of tasks in the warehouse environment.

A tuple defines each logistics task by its spatial location, workload requirement, deadline, and priority level. Therefore, the task is expressed as

$$T_k = (l_k, w_k, \tau_k, p_k) \tag{11}$$

where l_k is the position of task k in the warehouse environment, w_k is the workload or payload requirement associated with the task, τ_k is the time constraint or deadline for task completion, and p_k is the priority level of the logistics task.

In the swarm, each UAV agent is represented as a moveable aerial node with communication and logistic capabilities. The UAV state can be described as

$$U_i = (x_i, E_i, C_i, L_i) \tag{12}$$

where x_i is the spatial position of UAV i, E_i is the residual energy on board of the UAV, C_i is the communication relay capacity of the UAV node, and L_i is the UAV's logistics capability, including the maximum payload capacity.

To assign logistics tasks to UAV agents, a binary task allocation variable is introduced. Assignment variable x_{ik} represents whether UAV i is assigned to execute logistics task k. This variable is defined as follows:

$$x_{ik} = \begin{cases} 1, & \text{if UAV } i \text{ executes task } k \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

Using this allocation matrix, the UAV swarm's total logistics workload can be expressed as

$$W_{logistics} = \sum_{i=1}^{N} \sum_{k=1}^{M} x_{ik} w_k \tag{14}$$

where N represents the number of UAV nodes in the swarm.

Due to the severe energy constraints, the task allocation must meet the energy limitations for UAV platforms. The total energy consumption resulting from the assigned logistics tasks must not exceed the available onboard energy of each UAV. This constraint may be expressed as follows:

$$\sum_{k=1}^{M} x_{ik} E_k \leq E_i \tag{15}$$

where E_k is the energy required to accomplish task k.

For transport logistics tasks, limitations for payload must also be considered. Each UAV has a maximum payload capacity that depends on its propulsion and structure. Therefore, the following constraint must be met:

$$w_k \leq L_i \tag{16}$$

where L_i is the payload capacity of UAV i.

In addition to the logistics constraints, keeping the communication relay network connected when performing the task is necessary. A UAV swarm is a dynamic communication graph

$$G(t) = (V, E(t)) \tag{17}$$

where V is the set of nodes containing UAV relays and distributed antennas, and $E(t)$ is the time-varying communication links between the nodes.

The algebraic connectivity of the communication graph must be positive to ensure network connectivity. This condition is expressed in terms of the Laplacian matrix L of the communication graph as

$$\lambda_2(L) > 0 \tag{18}$$

where $\lambda_2(L)$ is the second smallest eigenvalue of the Laplacian matrix and is commonly known as the Fiedler eigenvalue. This constraint ensures that the movement of UAVs associated with logistics tasks does not interfere with the relay network's communication topology.

Because the UAV swarm must simultaneously support wireless communication and warehouse logistics operations, the optimization problem is described as a joint communication–logistics objective. In a single decision process, the proposed objective function considers signal quality, service coverage, logistics task completion, UAV energy consumption, communication delay, relay connectivity, and operational safety.

The global objective function is defined as

$$J(t) = w_1 Q_{comm}(t) + w_2 P_{cov}(t) + w_3 W_{logistics}(t) - w_4 E_{UAV}(t) - w_5 D_{net}(t) - w_6 C_{vio}(t) - w_7 S_{risk}(t) \tag{19}$$

In Equation 19, $J(t)$ denotes the UAV-assisted DAS architecture's global performance objective. The positive terms $Q_{comm}(t)$, $P_{cov}(t)$, and $W_{logistics}(t)$ represent desirable outcomes, namely, normalized communication quality, coverage probability, and completed logistics workload, respectively. In contrast, $E_{UAV}(t)$, $D_{net}(t)$, $C_{vio}(t)$, and $S_{risk}(t)$ are penalty terms associated with UAV energy consumption, network or task delay, relay-connectivity violation, and safety risk, respectively. All objective components are normalized to the interval [0, 1] to combine heterogeneous communication, logistics, energy, delay, connectivity, and safety indicators within a single optimization function.

The weighting coefficients satisfy the following conditions:

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 = 1, \quad w_i \geq 0 \tag{20}$$

which is a balance between the relative importance of communication performance, logistics efficiency, energy consumption, and delay.

The weighting coefficients w_1–w_7 determine the objective terms' relative importance. Specifically, w_1, w_2, and w_3 control the contribution of communication quality, coverage probability, and logistics workload completion, whereas w_4, w_5, w_6, and w_7 penalize UAV energy consumption, communication or task delay, relay-connectivity violation, and unsafe UAV movement, respectively. The weights are non-negative and sum to one, making the objective function interpretable as a normalized trade-off between communication reliability, logistics performance, energy efficiency, connectivity preservation, and operational safety.

Therefore, the optimization problem aims to maximize $J(t)$ by selecting UAV positions, relay links, and logistics task assignments that improve warehouse communication reliability while preserving energy efficiency, logistics performance, network connectivity, and UAV operational safety. This formulation differs from conventional UAV relay models in that it does not optimize communication performance alone; instead, wireless coverage, relay connectivity, delay, and logistics task execution are embedded into the same decision objective.

During operation, UAV agents dynamically update their positions when they perform assigned logistics tasks. The UAV motion dynamics can be approximated as

$$x_i(t+1) = x_i(t) + v_i(t)\Delta t \tag{21}$$

where $v_i(t)$ is velocity vector of UAV i and Δt is the control process's time step.

The movement decisions of UAV agents are determined using the reinforcement learning-based optimization framework described in the following subsection. Through unceasing interaction with the environment, UAV nodes learn to position themselves in places that simultaneously boost communication coverage and enhance logistics tasks.

The proposed UAV logistics model extends the conventional relay formulation by allowing UAVs to support communication and logistics tasks under energy, payload, connectivity, and safety constraints. The reinforcement-learning-based positioning model in Section 2.5 determines movement decisions under these coupled constraints (Boysen et al., 2019; Gu et al., 2010).

2.5 Reinforcement-Learning-Based UAV Positioning Algorithm

A reinforcement-learning-based positioning algorithm is used to support adaptive UAV relay deployment in GNSS-denied warehouse environments. The learning agent aims to determine UAV movement actions that improve wireless coverage and communication quality while limiting energy consumption, communication delay, connectivity loss, and unsafe motion near warehouse obstacles.

Each UAV is treated as an autonomous learning agent in the proposed framework. The UAV observes the current communication and operational state of the warehouse network at each decision step and selects a movement action. The learning problem is described as a Markov decision process (MDP) defined by the state space, action space, reward function, and transition dynamics.

The state vector of UAV agent i at time t is defined as follows:

$$s_i(t) = [RSSI_i(t), SINR_i(t), E_i(t), x_i(t), y_i(t), z_i(t), c_i(t), q_i(t)] \tag{22}$$

where $RSSI_i(t)$ is the received signal strength indicator, $SINR_i(t)$ is the signal-to-interference-plus-noise ratio, $E_i(t)$ is the residual UAV energy, $x_i(t)$, $y_i(t)$, $z_i(t)$ are the UAV coordinates, $c_i(t)$ is the local relay-connectivity indicator, and $q_i(t)$ is the local logistics-task status. The logistics-task status indicates whether the UAV is idle, assigned to inventory inspection, assigned to monitoring, or assigned to lightweight transport.

The action of the UAV is represented as a separate movement command:

$$a_i(t) \in \{hover,\ move + x,\ move - x,\ move + y,\ move - y,\ move + z,\ move - z\} \tag{23}$$

The UAV position is updated according to the following:

$$p_i(t + 1) = p_i(t) + \Delta p\left(a_i(t)\right) \tag{24}$$

where $p_i(t) = [x_i(t), y_i(t), z_i(t)]$ is the UAV position vector and $\Delta p(a_i(t))$ is the displacement associated with the selected action. Warehouse flight boundaries, safety margins, obstacle locations, and the allowable UAV altitude range constrain the feasible action space.

The reward function reflects the joint communication–logistics objective introduced in Section 2.4. At each time step, the reward is defined as follows:

$$R_i(t) = \lambda_1 Q_{comm}(t) + \lambda_2 P_{cov}(t) + \lambda_3 W_{log}(t) - \lambda_4 E_{uav}(t) - \lambda_5 D_{net}(t) - \lambda_6 C_{vio}(t) - \lambda_7 S_{risk}(t) \tag{25}$$

where $Q_{comm}(t)$ is the normalized communication quality, $P_{cov}(t)$ is the normalized coverage probability, $W_{log}(t)$ is the normalized completed logistics workload, $E_{uav}(t)$ is the normalized UAV energy consumption, $D_{net}(t)$ is the normalized communication or task delay, $C_{vio}(t)$ is the normalized relay-connectivity violation penalty, and $S_{risk}(t)$ is the normalized safety-risk penalty. The coefficients λ_1–λ_7 define the relative importance of each term and satisfy the following:

$$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7 = 1, \quad \lambda_i \geq 0 \tag{26}$$

The reward function uses positive and negative terms for desirable outcomes and operational costs, respectively. Communication quality, coverage probability, and logistics workload completion are rewarded, whereas energy consumption, delay, connectivity violations, and safety risks are penalized. This reward-shaping strategy prevents UAVs from improving signal quality at the expense of excessive movement, network disconnection, or unsafe operation near warehouse racks.

A Deep Q-Network (DQN) is used to approximate the action-value function $Q(s, a)$. The DQN receives the state vector as input and outputs the estimated Q-value for each feasible UAV movement action. During exploitation, the action with the highest Q-value is selected, while an ε-greedy policy is used during training to maintain exploration.

Table 1 summarizes the main DQN training settings, baseline strategies, and validation protocol. This compact table replaces separate configuration and validation tables to reduce redundancy while preserving simulation-based study reproducibility.

The evaluation protocol combines DQN-based UAV positioning, non-adaptive baseline comparisons, Monte Carlo simulations, robustness scenarios, and ablation settings. This protocol makes it possible to assess whether the observed performance gains result from the adaptive DQN policy rather than only from the physical addition of UAV relay nodes.

Training stability was evaluated by monitoring the moving average episode reward over a 50-episode window:

$$\overline{R}_k = \frac{1}{50} \sum_{e \in W_k} R_e \tag{27}$$

where $\overline{R}_k$ is the moving average reward at training interval k, and R_e is the obtained cumulative reward in episode e. Convergence was considered achieved when the moving average reward changed by less than 2% over 100 consecutive episodes. The DQN was trained offline in the simulation environment, whereas online deployment only requires a forward pass through the trained network for UAV action selection. Therefore, the proposed method is suitable for edge-assisted warehouse control.

Table 1 Methodological configuration and validation protocol

Aspect	Configuration used in this study	Purpose
DQN input state	RSSI, SINR, residual UAV energy, UAV coordinates, relay-connectivity indicator, and logistics-task status	Represents the communication, energy, position, connectivity, and logistics condition of each UAV agent
DQN action space	Hover; move $+x$; move $-x$; move $+y$; move $-y$; move $+z$; move $-z$	Defines feasible UAV movement decisions under indoor flight constraints
DQN architecture	Fully connected DQN with three hidden layers of 128, 64, and 32 neurons; ReLU activation; 7 output Q-values	Approximates the action-value function for adaptive UAV positioning
Training configuration	Adam optimizer; learning rate 0.001; discount factor 0.95; replay buffer of 50,000 transitions; mini-batch size 64; target network update every 100 steps	Provides stable offline training of the DQN policy
Exploration and training horizon	ε-greedy exploration; initial $\varepsilon = 1.0$; final $\varepsilon = 0.05$; 2000 episodes; maximum 500 steps per episode	Balances exploration and exploitation during policy learning
Baseline strategies	Static DAS only; fixed UAV relay placement; random UAV movement; heuristic shadow-zone placement; proposed DQN-based UAV positioning	Allows comparison between non-adaptive, heuristic, and learning-based positioning strategies
Monte Carlo validation	30 independent runs with randomized UAV initial positions, task locations, ground-node positions, and obstacle-shadowing conditions	Evaluates whether the results remain stable under different random seeds and warehouse layouts
Robustness scenarios	Low, medium, and high obstacle density; light, moderate, and heavy traffic load; co-channel interference; one-UAV relay failure	Tests the architecture under non-ideal warehouse communication conditions
Ablation settings	UAV relay nodes varied from 1 to 9; DAS antenna units varied from 4 to 8	Quantifies the influence of UAV swarm size and fixed DAS infrastructure density
Statistical reporting	Mean value, standard deviation, and 95% confidence interval	Provides uncertainty-aware reporting of simulation results

2.6 Simulation Protocol and Statistical Validation

The proposed system was evaluated using 30 independent Monte Carlo simulation runs for each configuration. In each run, UAV initial positions, logistics task locations, ground-node positions, and obstacle-shadowing conditions were randomized within the same warehouse geometry. The evaluation included three obstacle-density levels, three traffic-load levels, co-channel interference, one-UAV relay failure, and ablation tests with different UAV swarm sizes and DAS antenna densities.

The main performance metrics were average SNR, average SINR, coverage probability, throughput, latency, UAV energy consumption, logistics task completion time, and logistics task success rate. For each metric, the mean value, standard deviation, and 95% confidence interval were calculated as follows:

$$CI_{95} = \mu \pm 1.96 \cdot \frac{\sigma}{\sqrt{n}} \tag{28}$$

where μ is the sample mean, σ is the standard deviation, and n is the number of Monte Carlo runs. This protocol enables a reproducible comparison between the conventional DAS configuration, non-adaptive UAV relay strategies, and the proposed DQN-based UAV-assisted DAS architecture.

3. Results and Discussion

3.1 Signal Coverage Analysis

Reliable wireless coverage is an important requirement for communication systems deployed in GNSS-denied indoor transportation environments, where structural obstacles, metallic infrastructure, and multipath reflections strongly affect signal propagation. To assess the spatial performance of the proposed architecture, a coverage analysis was performed based on the simulation framework presented in Section 2.6. The received signal strength was calculated over the indoor environment by applying the propagation model defined in Section 2.2 and considering the antenna deployment configuration in Section 2.3.

The coverage analysis was carried out for the entire warehouse with a two-dimensional grid discretization with a spatial resolution of 1m × 1m. At the grid locations, the received signal power was calculated considering the contributions of the distributed antenna nodes and additional relay transmissions of the UAV nodes for the proposed architecture. Subsequently, the received signal strength was converted to signal quality measures using the SNR and SINR formulations.

Figure 2 shows the spatial distribution of the signal strength in the warehouse environment, which is the heatmap of the communication coverage obtained using the UAV swarm-assisted distributed antenna system.

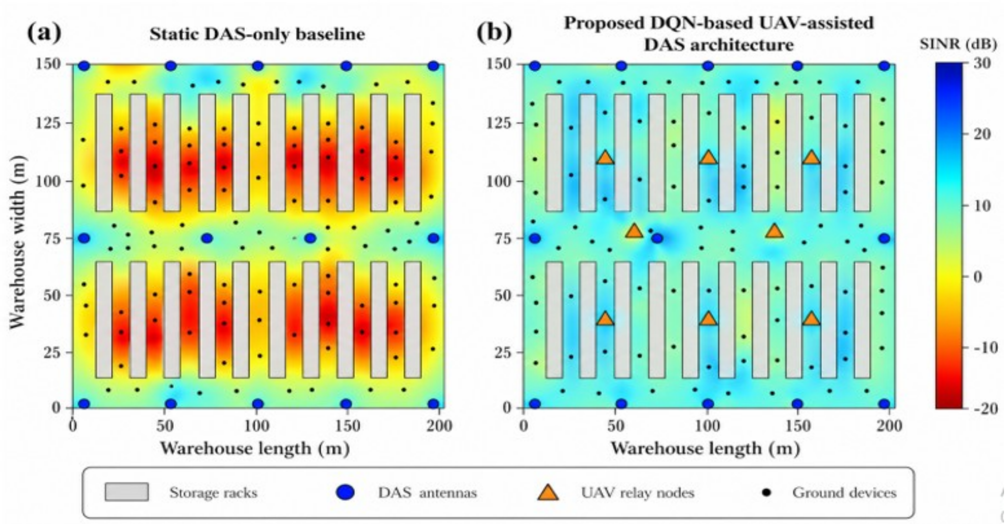


Figure 2 Comparative signal coverage heatmaps for the GNSS-denied warehouse environment: (a) static DAS-only baseline and (b) proposed DQN-based UAV-assisted DAS architecture. The color scale represents the SINR distribution across the warehouse area, whereas gray blocks indicate storage racks and regions with obstacle-induced shadowing

Figure 2 compares the static DAS-only baseline with the proposed DQN-based UAV-assisted DAS architecture. In the baseline case, low-SINR regions appear behind dense rack structures because fixed antenna units cannot dynamically compensate for obstacle-induced shadowing. In contrast, the proposed architecture reduces these low-coverage regions by positioning UAV relay nodes near shadowed areas. Quantitatively, the UAV-assisted system increases average received signal power by about 6–9 dB and raises the adequately covered service area from approximately 82% to over 96%.

3.2 Training Convergence and Positioning Behavior

The proposed DQN-based UAV positioning algorithm's convergence behavior was evaluated by tracking the moving average episode reward during training. The reward curve provides evidence that UAV agents gradually learned to improve communication coverage while reducing unnecessary movement, delay, and connectivity violations. At the beginning of training, the reward values fluctuated strongly because the UAV agents explored different movement actions. The moving average reward increased and then stabilized as training progressed, indicating that the learned policy converged toward a consistent positioning strategy.

The DQN-based strategy achieved more stable coverage improvement than random UAV movement and fixed UAV relay placement because UAVs were positioned near shadowed areas while maintaining relay connectivity with DAS nodes and neighboring UAVs. The heuristic shadow-zone placement strategy improved local signal strength, but it was less effective in balancing energy consumption, communication delay, and logistics-task constraints. These results indicate that the benefit of the proposed method is not only due to the presence of UAV relay nodes, but also due to the adaptive learning-based positioning.

The convergence result confirms that the improvement obtained by the proposed architecture is caused not only by the physical presence of UAV relay nodes but also by the adaptive positioning policy learned during training. The trained DQN policy can select movement actions according to the current communication state, UAV residual energy, relay-connectivity condition, and logistics-task status compared with random movement or fixed UAV placement. Therefore, the RL-based positioning strategy provides a more stable mechanism for maintaining coverage in GNSS-denied warehouse environments.

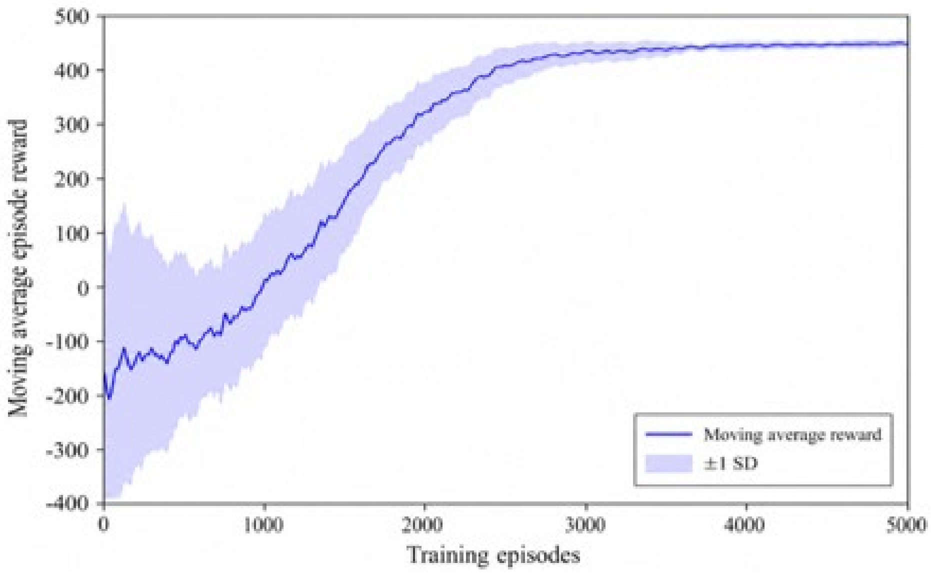
As shown in Figure 3(a), the moving average reward increases during training and stabilizes after the exploration stage, indicating that the DQN policy learns a consistent positioning strategy. Figure 3(b) further shows that as the number of UAV relay nodes increases, throughput improves and latency decreases, although the marginal gain becomes smaller after approximately five to seven UAVs. This confirms that the proposed system should be optimized by balancing swarm size, communication performance, energy consumption, and coordination overhead rather than simply increasing the number of UAVs.

3.3 Comparison of Network Performance

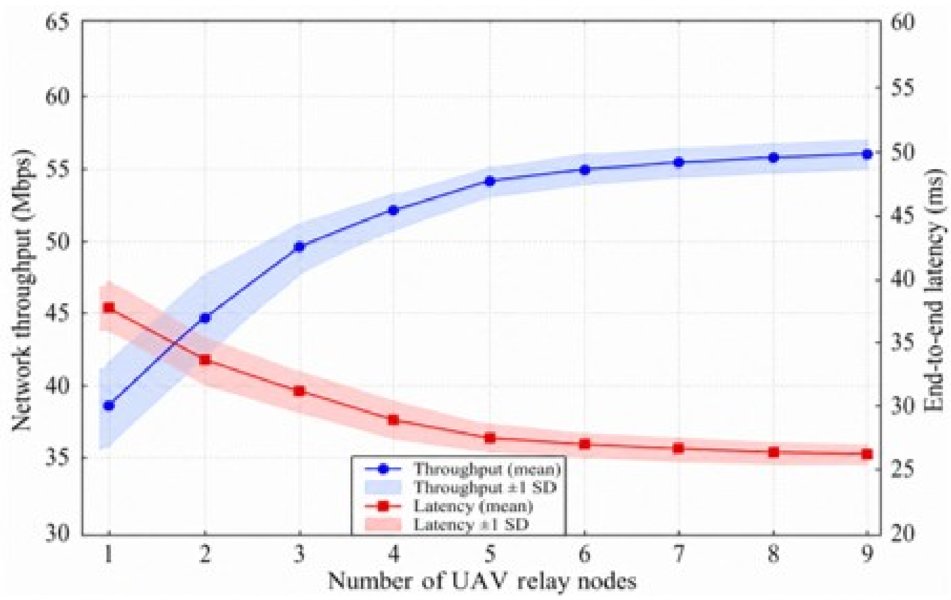
To further evaluate the proposed architecture, communication performance was assessed using 30 independent Monte Carlo simulations. The comparison included five configurations: static DAS only, fixed UAV relay placement, random UAV movement, heuristic shadow-zone placement, and the proposed DQN-based UAV-assisted DAS architecture. The results are reported as mean values with standard deviations and 95% confidence intervals calculated according to Equation 28.

Table 2 presents a statistical comparison of the evaluated communication architectures. The results are reported as mean values with standard deviations, and 95% confidence intervals are given in parentheses for the principal communication performance indicators.

Table 2 shows that the proposed DQN-based UAV-assisted DAS architecture achieves the highest SNR, SINR, coverage probability, throughput, and logistics-task success rate, while also providing the lowest latency. Compared with static, random, and heuristic relay deployment strategies, the DQN policy provides more stable performance because it balances coverage, delay, energy consumption, relay connectivity, and logistics-task progress.



(a)



(b)

Figure 3 DQN learning behavior and network performance trade-off: (a) training convergence of the DQN-based UAV positioning algorithm; (b) throughput–latency trade-off as a function of UAV swarm size.

3.4 Robustness and Ablation Analysis

Additional simulation experiments were conducted to evaluate the reliability of the proposed UAV-assisted DAS architecture under non-ideal warehouse conditions. The evaluation included different obstacle-density levels, traffic-load conditions, co-channel interference, UAV relay failure, reduced UAV swarm size, and reduced DAS antenna density. The purpose was to determine whether the proposed DQN-based UAV-assisted DAS architecture remains effective beyond the nominal simulation scenario. Table 3 summarizes the robustness evaluation under non-ideal warehouse scenarios. The results show that the proposed architecture maintains acceptable SINR, coverage probability, throughput, and latency values under all tested conditions.

Although performance decreases under high obstacle density, heavy traffic load, co-channel interference, and UAV relay failure, the degradation remains gradual rather than abrupt.

Table 2 Statistical performance comparison over 30 Monte Carlo runs, reported as mean ± standard deviation with 95% confidence intervals

Metric	Static DAS Only	Fixed UAV Relay	Random UAV Movement	Heuristic Shadow-Zone Placement	Proposed DQN-Based UAV-DAS
Average SNR (dB)	14.2 ± 1.1 (13.8–14.6)	17.6 ± 1.0 (17.2–18.0)	18.3 ± 1.4 (17.8–18.8)	19.8 ± 1.2 (19.4–20.2)	21.5 ± 0.9 (21.2–21.8)
Average SINR (dB)	11.8 ± 1.0 (11.4–12.2)	14.9 ± 1.1 (14.5–15.3)	15.6 ± 1.5 (15.0–16.2)	16.8 ± 1.1 (16.4–17.2)	18.7 ± 0.8 (18.4–19.0)
Coverage probability (%)	82.0 ± 2.8 (81.0–83.0)	88.4 ± 2.4 (87.5–89.3)	89.1 ± 3.1 (87.9–90.3)	92.7 ± 2.0 (92.0–93.4)	96.0 ± 1.5 (95.4–96.6)
Throughput (Mbps)	38.0 ± 2.6 (37.0–39.0)	46.7 ± 2.4 (45.8–47.6)	48.2 ± 3.0 (47.1–49.3)	52.4 ± 2.1 (51.6–53.2)	56.0 ± 1.9 (55.3–56.7)
Latency (ms)	42.0 ± 3.1 (40.8–43.2)	35.6 ± 2.8 (34.6–36.6)	34.8 ± 3.4 (33.5–36.1)	31.7 ± 2.5 (30.8–32.6)	28.0 ± 2.1 (27.2–28.8)
UAV energy consumption, normalized	–	1.00 ± 0.06	1.12 ± 0.08	0.91 ± 0.05	0.82 ± 0.04
Logistics task success rate (%)	–	86.5 ± 3.2	84.1 ± 4.1	90.3 ± 2.8	94.0 ± 2.1

Table 3 Robustness evaluation under non-ideal warehouse scenarios

Scenario	Average SINR, dB	Coverage probability, %	Throughput, Mbps	Latency, ms	Main interpretation
Nominal warehouse condition	18.7 ± 0.8	96.0 ± 1.5	56.0 ± 1.9	28.0 ± 2.1	Nominal baseline
Low obstacle density	19.6 ± 0.7	97.4 ± 1.2	58.3 ± 1.7	26.5 ± 1.8	Reduced shadowing
Medium obstacle density	18.7 ± 0.8	96.0 ± 1.5	56.0 ± 1.9	28.0 ± 2.1	Represents the nominal simulation condition
High obstacle density	16.4 ± 1.1	91.8 ± 2.3	50.6 ± 2.6	34.2 ± 2.9	Higher blockage
Light traffic load	19.1 ± 0.8	96.8 ± 1.3	57.4 ± 1.8	25.9 ± 1.9	Low queuing
Heavy traffic load	17.2 ± 1.2	92.6 ± 2.4	49.8 ± 2.9	36.7 ± 3.4	Higher queuing
Co-channel interference	15.8 ± 1.3	89.7 ± 2.8	47.5 ± 3.1	38.4 ± 3.6	Interference penalty
One UAV relay failure	16.9 ± 1.1	92.3 ± 2.2	51.2 ± 2.7	33.6 ± 2.8	Relay redundancy

The ablation results show that increasing the number of UAV relay nodes improves SINR, coverage probability, and throughput up to a saturation point. The largest gain is observed when the swarm size increases from one to five UAVs. After five to seven UAVs, the performance curves become flatter, indicating that additional UAVs provide smaller marginal gains because of overlapping relay coverage and increased coordination overhead.

Figure 4 visualizes this saturation behavior by showing the coverage probability, throughput, and latency trends as the UAV swarm size increases. These results indicate that the proposed system should not be optimized only by increasing the number of UAVs. Instead, UAV count, DAS density, energy consumption, and coordination overhead should be jointly considered during practical deployment. Table 4 summarizes the ablation analysis of UAV swarm size and DAS antenna density.

Table 4 Ablation analysis of UAV count and DAS antenna density

Configuration	Average SINR, dB	Coverage probability, %	Throughput, Mbps	Latency, ms	Interpretation
DAS only, 6 antennas, 0 UAV	11.8 ± 1.0	82.0 ± 2.8	38.0 ± 2.6	42.0 ± 3.1	Baseline
DAS + 1 UAV	14.1 ± 1.3	86.5 ± 2.7	43.2 ± 2.8	38.6 ± 3.0	Single-relay limit
DAS + 3 UAVs	16.7 ± 1.1	91.4 ± 2.1	50.1 ± 2.4	33.4 ± 2.5	Multi-hop benefit
DAS + 5 UAVs	18.7 ± 0.8	96.0 ± 1.5	56.0 ± 1.9	28.0 ± 2.1	Best trade-off
DAS + 7 UAVs	19.2 ± 0.9	96.8 ± 1.4	58.7 ± 2.0	27.4 ± 2.0	Small marginal gain
DAS + 9 UAVs	19.4 ± 1.0	97.1 ± 1.5	59.3 ± 2.2	27.2 ± 2.2	Saturation
4 DAS antennas + 5 UAVs	17.4 ± 1.2	92.8 ± 2.3	51.6 ± 2.8	33.1 ± 2.7	Reduced DAS density
8 DAS antennas + 5 UAVs	19.5 ± 0.8	97.2 ± 1.3	58.9 ± 1.8	26.8 ± 1.9	Higher infrastructure cost

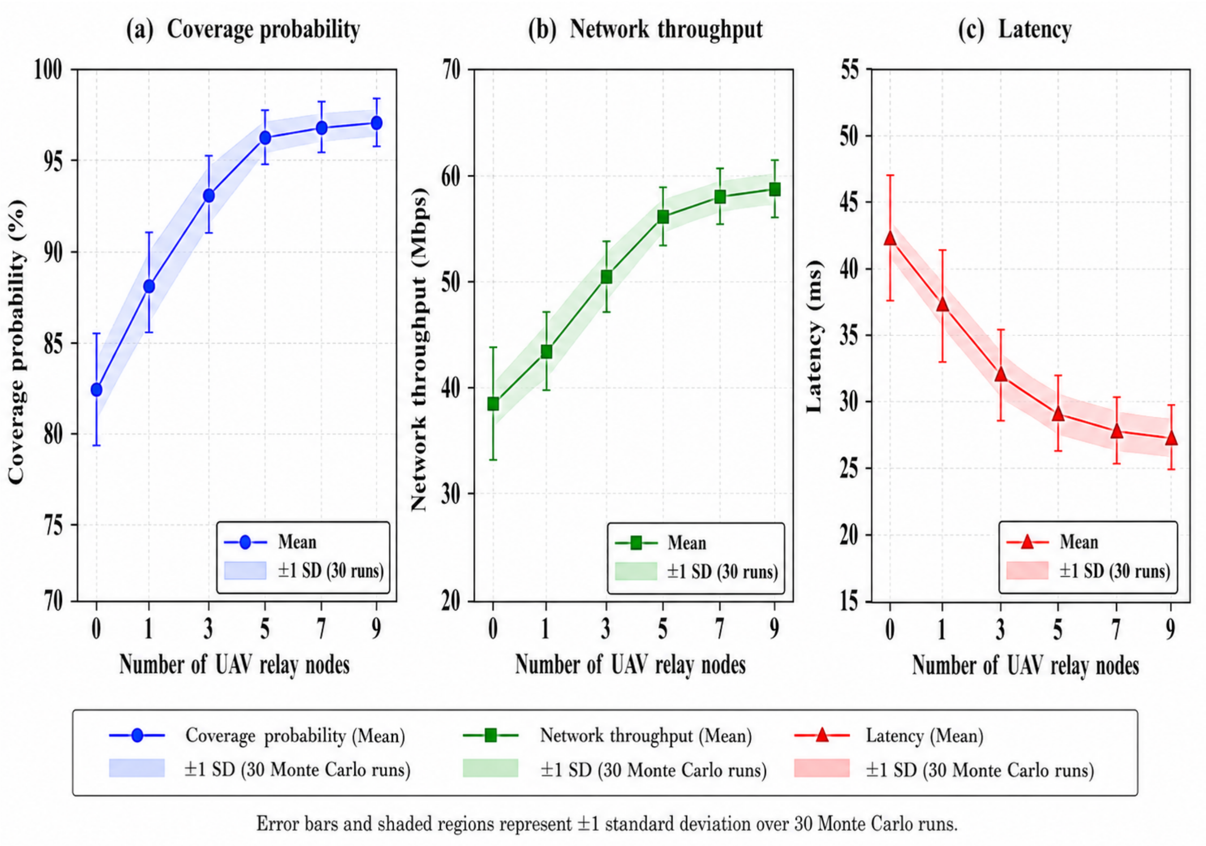


Figure 4 Ablation analysis of the UAV swarm size showing the coverage probability, throughput, and latency trends under repeated simulation runs

3.5 Operational Performance: Throughput, Energy, and Logistics

The proposed DQN-based UAV-assisted DAS architecture improved throughput from 38 to 56 Mbps and reduced latency from 42 to 28 ms compared with the static DAS-only baseline. This improvement is explained by adaptive relay paths that reduce communication distance and compensate for obstacle-induced shadowing.

Propulsion accounted for approximately 65–70% of total UAV energy consumption. However, the DQN-based positioning approach reduced unnecessary movement by keeping UAVs near communication-constrained regions. As a result, propulsion energy use decreased by approximately 18% compared with a predefined patrol strategy. The logistics-task success rate also increased from 81% to 94%, while the average task execution time decreased from 48.5 s to 37.2 s.

3.6 Engineering Discussion and Practical Implications

The results show that the main benefit of the proposed architecture is the adaptive coordination between fixed DAS infrastructure, UAV relay nodes, and logistics-task execution. Unlike static DAS deployment, the UAV relay layer can reposition itself toward communication-constrained areas and form alternative multi-hop links between ground devices, DAS antennas, and the warehouse controller. This explains the observed improvements in SINR, coverage probability, throughput, latency, and logistics-task success rate.

From an implementation perspective, the proposed system should be considered an adaptive extension of fixed DAS infrastructure rather than a replacement. Practical deployment still requires safety-aware flight control, collision avoidance, restricted flight zones, battery management, and validation in a physical warehouse-like environment. Therefore, the present simulation results should be interpreted as simulation-based feasibility evidence rather than real-world deployment performance.

4. Conclusions

This study proposed an integrated UAV swarm-assisted DAS architecture for improving wireless communication and supporting drone logistics operations in GNSS-denied smart warehouse environments. The proposed framework combines fixed distributed antenna infrastructure, adaptive UAV relay nodes, and reinforcement-learning-based positioning to improve communication coverage, signal quality, latency, and logistics task support under challenging indoor propagation conditions.

The simulation results indicate that the proposed system can improve communication and logistics performance under the GNSS-denied warehouse scenarios. The results of this research imply the possibility of using UAV swarm-based communication infrastructures to build next-generation intelligent logistics systems. By combining aerial relay nodes and distributed antenna networks, flexible and resilient communication architectures that can operate in complicated indoor environments can be designed.

Future research will focus on experimental validation using real UAV platforms, indoor wireless communication modules, and warehouse-like test environments. Further work should investigate UAV charging strategies, safety-aware indoor flight control, edge-based inference, distributed multi-agent learning, and cost-performance optimization. These extensions are necessary to move the proposed framework from simulation-based feasibility analysis toward practical industrial deployment.

Acknowledgements

The authors would like to thank their institutions for providing academic and technical support during the preparation of this study.

Funding

This research received no external funding.

Author Contributions

Conceptualization, G.I. and K.T.; methodology, R.U.; software, K.T.; validation, A.T., I.N. and R.U.; formal analysis, K.T.; investigation, N.Z.; resources, I.N.; data curation, A.T.; writing—original draft preparation, G.I.; writing—review and editing, A.T.; visualization, K.T.; supervision, I.N.; project administration, N.Z.; funding acquisition, G.I.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of AI

The authors declare that artificial intelligence tools were not used to generate the scientific content, research methodology, simulation data, data analysis, results, or conclusions of this manuscript. AI-assisted tools were used only for visual layout refinement and language polishing. All scientific interpretations, numerical results, and final manuscript content were reviewed and approved by the authors.

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