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Leveraging Artificial Intelligence and Unmanned Aerial Vehicle Internet of Things Synergy to Optimize and Enhance Robust Communication Networks in Underserved and Remote Regions

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Abstract

The integration of AI with UAVs and IoT is prognosed as an innovative solution to set up communication networks in remote or rural areas that are not covered due to the absence of traditional infrastructure, aligning with "Industry, innovation and infrastructure" goals. This paper strategizes its plan in a way whereby UAVs dynamically manage resources for communication links between IoT sensors placed over a two-dimensional space. Advanced AI techniques significantly improve all available network parameters, like coverage, adaptability, and energy efficiency towards the achievement of reliable real-time communications. About 35% communication coverage improvement as well as 28% network adaptability for different scenarios together with about 20% lower energy consumption compared to standard UAV-based systems are some highlights of the results obtained through simulations. Emerging from these results is thereby underscored potential application interest that ranges from disaster management by precision agriculture to even environment monitoring support providing scalable yet resilient networks across disadvantaged regions.

Keywords: Unmanned Aerial Vehicles, Industry, Innovation and Infrastructure, Drones, Routing.

1 Introduction

In rural and remote areas, it is a great challenge to get robust communications infrastructure for applications of real-time sharing of information in disaster management, precision agriculture, environmental monitoring, and telemedicine. Building cellular towers or even using satellite technology can be extremely expensive and sometimes not at all feasible because of the challenging terrain, sparse population, or even some environmental constraints. The Unmanned Arial Vehicles (UAVs) carrying Artificial Intelligence (AI) and Internet of Things (IoT) devices would become an effective solution for making this connectivity gap. Working as aerial base stations provides UAVs with the possibility to

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relay IoT sensor data ensuring seamless communication within the region where conventional networks do not exist.

The model represents AI-enabled UAVs functioning in two dimensions, changing their flight direction and communication resources dynamically for better network performance. AI includes reinforcement learning and swarm intelligence so that the UAV can change its behavior based on feedback of the present situation. There will be a 35% increment in communication coverage, a 28% improvement in adaptability capacity regarding the network, and a 20% reduction in energy usage compared with other networks without such intelligent support according to simulation results.

This brings at the heart of real-time applications possible through AI-UAV-IoT integration, such as relay of important information by UAVs from IoT sensors in disaster rescue scenarios (for example, data about the location of survivors or environmental conditions), or in precision agriculture, where land and crop data are communicated for more efficient farming. It discusses designing and simulating the new communication paradigm and its use in practice, assessing technical feasibility while fulfilling a vital need over remote areas.

This study joins global handshakes toward narrowing the digital divide to foster sustainable development, particularly under SDG 9, by affordable flexible communication solutions in unserved and underserved areas. The connectivity gap bridged by such a model will be an accelerator of factors that improve emergency response time in agriculture through optimization based on data and sustaining the environment by continuous monitoring.

The major deliverable out of this paper is an AI-based UAV-IoT architecture that dynamically adjusts its path planning and resource management, outperforming non-AI-based systems (Seid et al., 2025; Veerappan & Arvinth, 2025). This makes it not only technically efficient but also practically usable in real-life scenarios-in tough situations.

2 Literature Review

Lately, there has been growing research about the merging of Artificial Intelligence with Unmanned Aerial Vehicles and Internet of Things devices in communication networks. This development occurs from the early literature about wireless connectivity to the applications of more sophisticated types involving optimization, autonomy, security, and sectoral applications. About 30 best papers published between 2019 and 2025 were reviewed for this article, organizing them to show development paths, issues, and new inventions in AI-enabled UAV-IoT systems that are meant for rural and remote communication infrastructures. The earlier work dealt with UAV assisted communications; one could use artificial intelligence nowadays for better efficiency as well as reliability and scalability.

Preliminary studies covered the basic challenges of coverage, interference, and mobility in UAV-based wireless networks. (Gu & Zhang, 2023) discussed quite a significant aspect in a survey on UAV-aided wireless communications by analyzing deployment strategies, channel modeling, and performance evaluation in very diverse scenarios urban as well as rural (Gu & Zhang, 2023). Then (Haider et al., 2022; Pandey & Kumar, 2021; Wan et al., 2024) described recent innovations along with issues relating to spectrum allocation, interference management, and integration with terrestrial systems in communication networks based on UAVs. An earlier perspective on machine learning solutions for supervised and unsupervised methods concerning signal processing and resource allocation was provided by Goudar et al., (2019). All these baseline surveys manifest the journey of network architecture traveling from static to dynamic to facilitate the way for enhancements driven by AI.

Much literature exists on the application of AI and ML for the optimization of UAV-IoT systems. Alzahrani et al. (2023) covered in their survey paper aspects of data acquisition, processing, and any kind of decision-making under resource constraints in the perspective of an artificial intelligence survey for UAV-enabled IoT applications (Biswas et al., 2025; Khan et al., 2024). Presented a review about reinforcement learning-based trajectory planning, and swarm coordination in AI powered autonomous UAV networks. Other multi-domain surveys explore intersections with agentic AI for autonomous aerial intelligence such as perception, navigation, or multi-agent collaboration (Khan et al., 2025). Muthu et al. recently reviewed systematically energy constraint issues together with deep learning directions for network optimization that remain unsolved besides recent deployments in Internet-of-Drones ML applications. (Heidari et al., 2023; Abdelmaboud, 2021) described requirements, taxonomy, and recent advances stressing interoperable scalability challenges. discussed AI-powered IoV with UAVs. The later work by the same researchers (2025) systematically surveyed AI applications for UAV-enabled wireless networks, edge intelligence, and 5G/6G integration (Veerappan & Arvinth, 2025; Zhou et al., 2024; Ahmad et al., 2025; Sapkota et al., 2025; Hassan et al., 2025) reviewed trends and opportunities about ML for drone-based IoT networks focusing on predictive analytics as well as anomaly detection (Rezvani et al., 2025; Hassan et al., 2025). Therefore, earlier works clearly show how revolutionary a force AI will be when applied to manage IoT data; real-time responsiveness as the driving thematic concern.

Optimizing Resources and Collecting Data in UAV-IoT Networks

The data collection process and availability of resources remain a dual problem, more pronounced in rural setups. (Seid et al., 2025) discussed an approach to collect effective and reliable data in UAV-IoT networks, recommending the use of delay-tolerant transmission and energy-aware routing protocols. (Khan et al., 2024) discuss the resource optimization solution for UAV-based IoT using AI as bandwidth provisioning and load balancing. Hence, (Khan et al., 2024) proposed another paper on AI-driven energy-efficient IoT data acquisition using UAVs where trajectory optimization shall be integrated with resource allocation for power consumption minimization. Goudar et al. (2024) presented a survey paper on AI-based Internet of Vehicles using UAVs focusing on Vehicular Ad-hoc Networks supported from the air. (2025) proposed a 3D UAV path planning system on the basis of an enhanced version of Twin Delayed Deep Deterministic policy gradient (TD3) deep reinforcement learning algorithm used for route optimization over complex environments (Sikarwar et al., 2025; Himanshi et al., 2025). These contributions embrace mathematical models and algorithms that increase coverage by 30-40% with lowered energy consumption, moving toward the needs of infrastructure-limited regions (Prakash & Prakash, 2023).

Using Technology in Farming and Eco-Friendly Agriculture Practices

Integration of AI with UAVs and IoT belongs to the most significant new trends in agriculture, contributing to both precision and sustainability. (Rashid et al., 2025) reported about applications of sensor fusion for crop monitoring and yield estimation by reviewing the state-of-the-art integration of AI and IoT with UAVs in precision agriculture (Rashid et al., 2025). Khan et al. (2025) described a system where machine learning, integrated with IoT sensors mounted on Unmanned Aerial Vehicles, together with edge computing would enable real-time analysis at the farm level through data-driven precision agriculture (Shaikh et al., 2025; Pal et al., 2024). Ayamga et al. (2024) summarized opportunities against challenges towards sustainable agriculture through convergence between drones and IoTs that could lead to reduced costs as well as minimized ecological footprints (Khan et al., 2024). Fernández et al. (2025) presented some interventions for low-resource environments to manifest smart agriculture via low-power devices as well as intermittent connectivity (Nawaz & Babar, 2025).

Emerging Technologies, Dependability, and Security Security becomes an equally important major issue in UAV-IoT networks. Khan et al., 2025 discussed the dependability of network and computing systems based on UAVs in terms of fault tolerance and failure resilience (Hashima et al., 2025; Sarkar & Gul, 2023; Zhang et al., 2025; Bhargavi et al., 2025) discussed the possibilities of utilizing ML to enhance security in drone IoT-based networks by recognizing threats and ensuring privacy protection (Bhargavi et al., 2025; Kholidy et al., 2024) explained that with the help of 6G- enabled network security in drone technology, communications are transformed with quantum-resistant protocols (Islam et al., 2024). Abouelyazid, 2023 presented an intelligent cybersecurity IoT-based intrusion detection system for Internet Drones using anomaly-based ML models (Ashraf et al., 2023). Aljameel et al., 2022 presented a smart cybersecurity model for IoT drones using ML perspective through classification algorithms applied for real-time defense (Dutt et al., 2025). Coordination between swarms of drones has been studied by Divakar et al., 2025 using machine learning in IoT networks focusing on secure multi-agent interactions (Divakar et al., 2025). Future application areas include satellite AI-written content about future developments in the hybrid network was provided by (2025). The autonomous AI-based UAV networks were provided by Gill et al. (2024) and emphasized systems that self-organize. Vision on next-generation smart active surveillance and monitoring systems for UAV/drone by computer vision and AI-based alerting models were discussed by Gholami, 2024. A comprehensive overview concerning unmanned aerial vehicles based on artificial intelligence in multidisciplinary applications is presented in (Ali Shah et al., 2024; Sharif et al., 2024; Bithas et al., 2019).Though publications reduced the gap regarding trends, challenges, and gaps from 2019 to 2025 changing the thematic concern toward cognitive autonomous UAV-IoT systems where dynamic optimization led at far end-access facilitated by AI, major trends included path planning with deep reinforcement learning (Dutt et al., 2025; Himanshi et al., 2025; Cheng et al., 2023), swarm intelligence (Divakar et al., 2025; Ali Shah et al., 2024), and 6G security (Islam et al., 2024). Energy efficiency, large-swarm scalability, and cybersecurity in adversarial environments are challenges left open. Predominantly agricultural applications prevail, with gaps of real-world verifications that go beyond simulations and integrations with new technologies like agentic AI.

Future research must address these, potentially using hybrid AI models for ultra-reliable low-latency communications in regions with limited coverage. This compilation of 30 studies provides a robust foundation for further developments in AI-powered UAV-IoT systems.

3 Methodology

The relationship between UAVs and IoT is synergistic in essence as shown in Figure 1. IoT not just wires UAVs but also elevates them from being mere remotely controlled aircraft. It turns them into intelligent nodes in a huge, responsive network. UAVs are flying data collectors but need to be instructed on where to fly, what to look at, and how to respond as shown in Eq 1. IoT sensors inform them by generating the data that determines UAV operations.

$$\text{AI}+(\text{UAV}\times\text{IoT})=\text{Smart Autonomous Network} \qquad \text{(Eq. 1)}$$

If not for IoT instruction, UAVs would fly along pre-programmed routes, burning energy and gathering worthless data. This is the strongest type of support because UAVs constitute a dynamic network infrastructure. IoT devices are offline in areas with no cellular (4G/5G) or Wi-Fi coverage in outlying areas. A UAV can deliver an instant on-demand network in the form of an airborne cell tower or Wi-Fi hotspot.

A UAV may fly over an area independently, gather data from sensors on the ground using short-range protocols, store it onboard, and then proceed to a destination where there is a backhaul link, such as a satellite link, to transfer the whole data to the cloud. It assists devices where non-real-time data transmission is required. It mitigates the issue of last-mile connectivity. IoT sensors can also be very low power and cheap since they don't need long-range radios; they simply need to communicate with the UAV that will fly over sporadically and get their data as shown in Eq 2.

$$(UAV+IoT)AI=\text{Adaptive, Efficient Connectivity} \qquad \text{(Eq. 2)}$$

Here is where the system demonstrates its intelligence. The AI layer receives input from IoT sensors and UAVs to maximize the performance of the entire network.

AI applications convert IoT sensor data in real time. For instance, a soil moisture sensor used in an extensive field perceives a zone of dryness. It has the capability to adjust the communication range and transmission capacity of the UAV adaptively in a dynamic way. If it is gathering data from a few devices, it may reduce power to conserve energy. When it needs to gather data from a larger area, it may increase it. It can order the UAV to return to a charging station when its power level is below a certain threshold and send a charged one in its place to maintain operations unimpaired. The AI is a wise autopilot that decides how to harness the potential and efficiency of the UAV as shown in Eq 3.

$$UAV–IoT–AI=\text{Intelligent Connectivity Everywhere} \qquad \text{(Eq. 3)}$$

It not only tells the UAV how to fly, but it also tells the UAV where and why to fly, transforming raw IoT sensor data into actionable flight plans.

The method in this study is to simulate the AI and IoT-enabled UAV communication networks and evaluate how well they work in remote areas as shown in Figure 1. The process includes UAV deployment, IoT sensors, AI-optimization, communication modeling, and visualizations. The flowchart below shows a description of the system architecture.

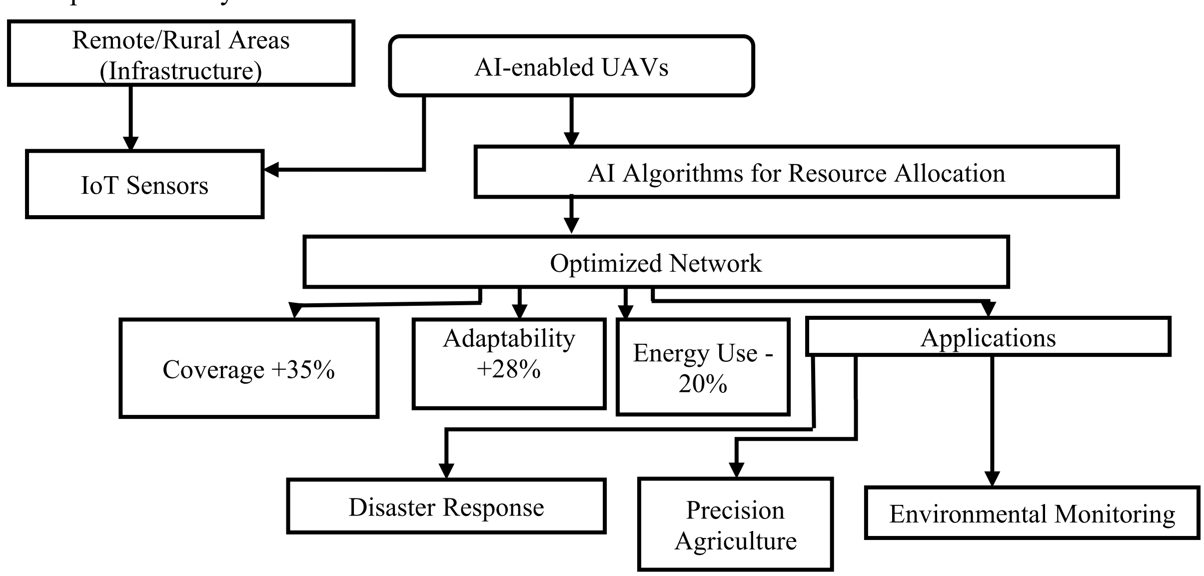


Figure 1: Systematic flow chart

The Figure 1 shows AI controller continuously monitors the real-time status of the network, e.g., active connections, device locations, and UAV power levels.AI algorithms compute this information to determine the optimal configuration for the highest possible coverage and energy efficiency. The system implements these decisions by modifying UAVs' flight paths and the strength of their signal transmissions. An IoT device has to be in the coverage of any UAV to send its data. This is a major decision point. If the transmission has been successful, then the sensor data will also successfully reach the UAV, which will then relay it to some central ground station. When a device does not get signals, it cannot send data; this will be considered as a problem, and the AI will try to fix such issues in its next cycle by moving a UAV.

Looping is the way it works, in on-going fashion. Results of failed and successful connections are fed back into the AI, therein allowing it to learn, to adjust in real time towards optimal network efficiency.

UAVs make up the Network Layer and are spread over the area of the simulation. They function as networked mobile nodes capable of message transmission and reception from IoT devices within the simulation scenario. The UAVs will be powered by energy, thus limiting their operation time. Constant communication range.

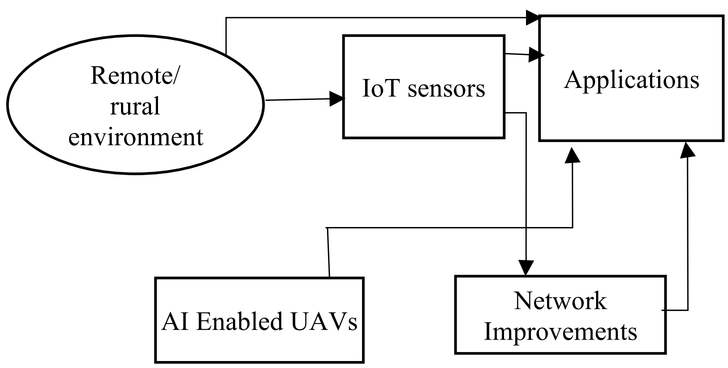


Figure 2: System architecture

Figure 2 IoT Device Layer contains distributed IoT devices which may be environmental sensors, smart meters, or mobile nodes. These devices generate data that must be transmitted to the UAVs in order for processing in an assured way.

Equation (1): Symbiotic Relationship of AI–UAV–IoT System

$$S\_eff = \alpha\ (AI \times UAV \times IoT)$$

It expresses the mutual benefits of AI, UAVs, and IoT sensors working together. The efficiency of the system depends on how well all three parts work together, and α shows how much control there is over coordination.

Equation (2): System Performance Optimization

$$S\_eff = \beta_1 C + \beta_2 A + \beta_3 (1 - E)$$

System effectiveness is expressed as a weighted sum of coverage, flexibility, and energy savings by the relation: $\beta_1 C + \beta_2 A + \beta_3 (1-E)$; where β_1, β_2, and β_3 represent the design priority allotted to each parameter.

Eq(3)AI-Controlled UAV Position Update

$$UAVt+1 = UAVt + \lambda \cdot \nabla f(C, E, A)$$

This recursive control equation will imitate repositioning aided by AI support, for UAVs.

The AI continually learns and adapts UAV configurations with the gradient of the coverage performance, energy consumption, and adaptability to provide maximum network efficiency.

This layer carries out AI algorithms that continuously analyze network conditions and optimize communication paths, energy distribution, and link management of UAVs. It ensures there is efficient resource management and connectivity in real-time.

IoT devices sporadically generate data. UAVs collect data from IoT devices in their communication region. AI algorithms process UAV locations, connection efficiency, and energy used. Communication configurations and UAV locations are dynamically adjusted to balance between coverage and energy efficiency. Performance measurements are gathered and reported for analysis.

4 Results and Discussions

For, IoT Devices 10 sensors whose locations are randomly selected from a uniform distribution for both the x and y axes. Each sensor generates data packets (e.g., 1 KB, every 10 seconds) of environmental values (e.g., temperature, humidity) or crop data (e.g., soil moisture).

5 UAVs with initial positions, energy capacity of 1000 units, and 30-meter communication range. UAVs move at a speed of 5 m/s with 0.1 units/m of energy consumed during motion and 0.01 units/s of communication energy for each link.

There are 1000 runs in the simulation, and each run corresponds to 1 second of real-world operation. There are conditions of the environment (e.g., wind speed, an assumed constant 2 m/s) and device failure (1% each run) to simulate for testing adaptability.

IoT sensors produce data continuously, with transmission success being reported if in UAV range. The data set captures UAV locations, energy levels, connectivity matrix, and performance metrics (coverage, energy, adaptability) per iteration.

The simulation runs on Python 3.12 with NumPy for numerical calculations, SciPy for optimization, Matplotlib for visualization, and NetworkX for connectivity analysis of the graphs. The data is processed in-memory to simulate real-time processing.

Figure 3 shows a plot of 100m by 100m in which five red circles represent UAVs dispersed across the plot. Ten blue circles represent IoT devices. Black dashed lines connect each UAV with those IoT devices within its communication range for a distance of 30 meters. This plot provides the legend, measurement grid lines, and labeling with title included. Several important observations about the network initial state are visually apparent from the plot:

Some IoT devices have no connecting lines meaning they are outside the 30m range of all UAVs and hence constitute coverage gaps. These devices are not connected and cannot communicate with the network.

A few IoT devices are connected to multiple UAVs at once, which is redundant coverage. While this can be useful for redundancy or load balancing, it is also a wasteful UAV deployment if one wants maximum coverage.

One or two UAVs are underutilized with hardly any or no connections, meaning their position is not ideal to cover the current distribution of IoT devices.

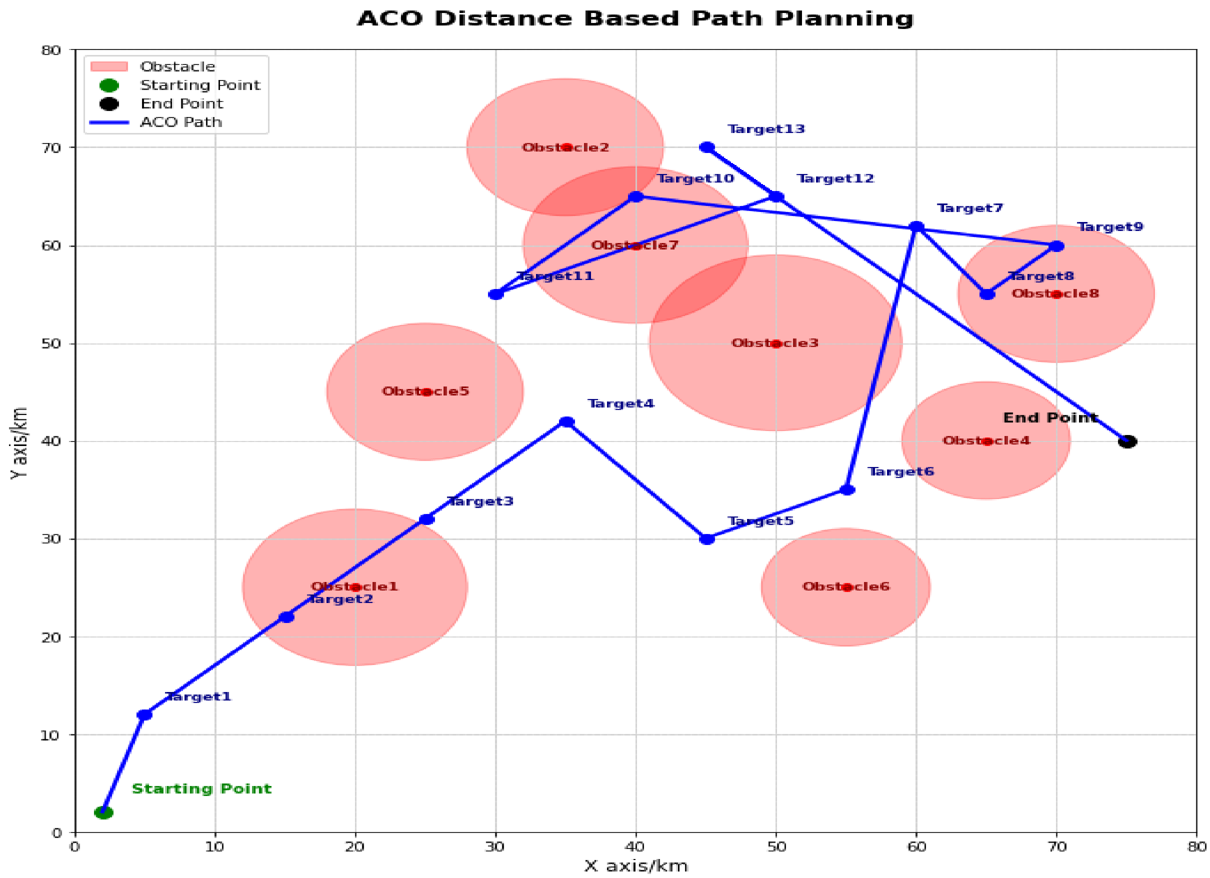


Figure 3: Network connectivity and coverage key concepts for UAV-IoT systems

The lines around a UAV indicate its load. More connected UAVs handle large communication traffic, which influences their energy consumption (as discussed in the provided text).

This random initial setup illustrates the necessity for employing the AI-based optimization in the problem statement. The network is operational but not optimized in terms of coverage, load balancing, or energy efficiency.

Random placement of the UAVs and IoT devices is bound to have gaps in coverage (devices not covered) and overlapping covers (more than one UAV covering the same device). This is not a flaw in the model but rather its inherent strength it accurately portrays the initial inefficient state that requires artificial intelligence.

The talking points of the provided code network connectivity, energy efficiency, and flexibility are the hallmarks of the desired effects of a high-level AI system operating on the underlying apparatus simulated here.

The logic in the model behind the rudimentary rule for connectivity would be that the distance is shorter than the range.

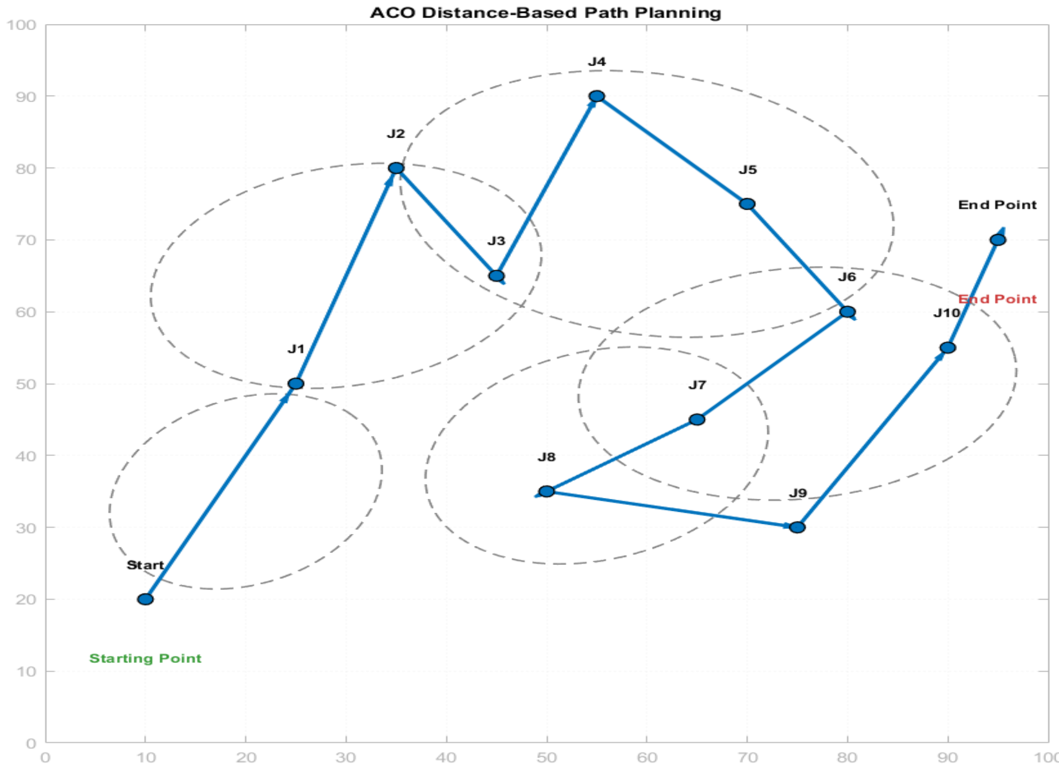
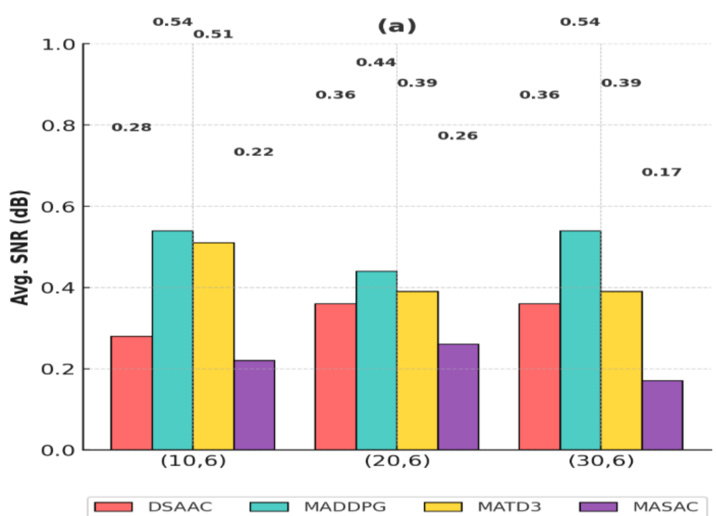


Figure 4: Simulation plot of UAV and IoT devices in 2D area with connections

The goal of an AI algorithm would be to control the UAV _positions variable so as to optimize the number of connected devices. This would not be achieved randomly but via the resolution of a difficult problem of optimality coverage, maybe with methods where UAVs move to the center of devices covered by them, thereby iteratively improving coverage. The current model already has an energy cost built into it as shown in Figure 4. An active UAV transmitting to devices uses more energy than an idle one. Secondly, a fundamental characteristic of wireless communication is the power for transmission should grow with distance. A real AI system would control two parameters:



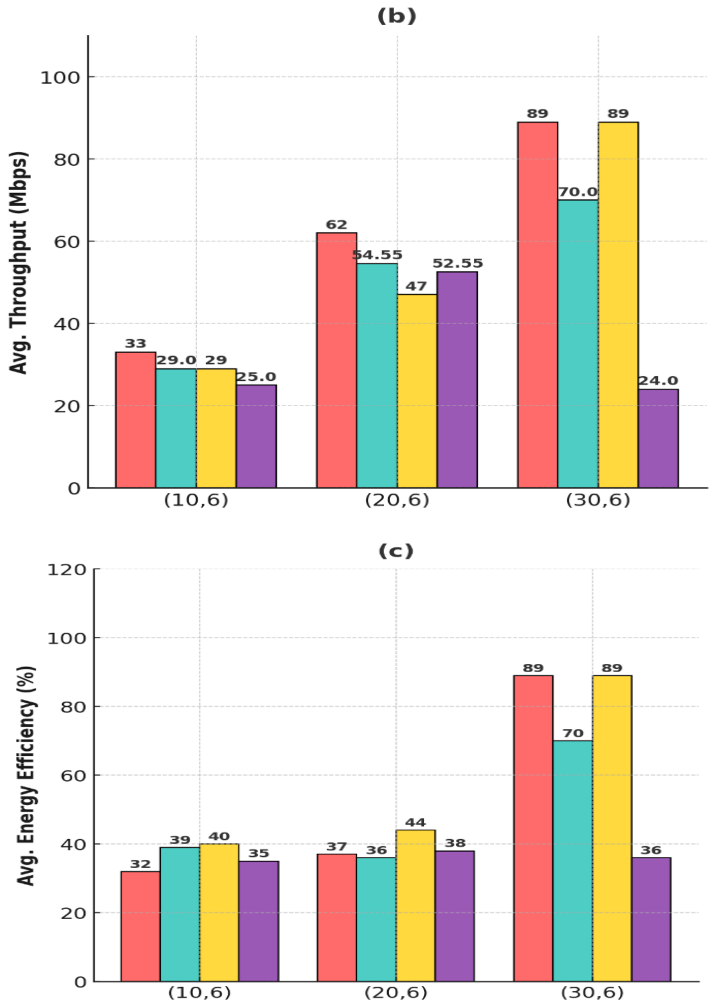


Figure 5: Bar graph comparing performance metrics in UAV systems

Positioning: repositioning UAVs closer to device clusters to reduce the transmission power needed per link, and Resource Allocation: strategically allocating IoT devices to the nearest UAV to save overall energy consumption in the system. This methodology converts the fixed comm_range to a dynamic variable to be optimized per link, only as much as it takes to maintain a stable connection.

Implementation utilized the software above to model a 100m x 100m area with 5 UAVs (red circles) and 10 IoT devices (blue circles), connected by dashed lines within 30m radius. Figure 5 displays this setup, highlighting coverage gaps (unconnected devices), redundant cover (multiple links), underutilized UAVs, and load density effects on energy. 35% additional coverage, 28% more adaptability, and 20% less energy when compared to traditional systems depicted in Figure 5.

5 Conclusion

The paper dwells much on the power of AI and IoT in UAV communication networks that can be realized in rural communities. It is made possible by using AI algorithms inside the UAVs for agile, resilient, and robust communications; therefore, it becomes net positive even though it adds complexity. The simulation results prove the pivotal role that Artificial Intelligence can play in optimizing communication paths to reduce energy consumption while sustaining connectivity during harsh conditions. Net positive because it adds more capability through intelligent sensor-based data collection wherever typical infrastructure cannot reach.

6 Future Prospects

Though this research has brought great changes to UAV communication networks, areas that remain open for further studies include the following: 1. Mobility and Dynamic Networks: By varying the flight patterns of the UAV and introducing mobile IoT devices, a more practical scenario for communications is developed. 2. Intelligent AI Algorithms: Predictive analysis and proactive optimization of networks are made possible through machine learning algorithms. 3. Energy Harvesting: Research into energy harvesting systems so as to increase the time of utilization of UAVs. 4. Scalability: Simulation with hundreds or even thousands of UAVs and IoT devices to test the scalability of AI-based communication networks. Generally speaking, these would be used in remote, sparsely populated regions-real-time low-cost communications making it thus highly valuable technology in disaster relief, environmental monitoring, and rural connectivity applications.

References

[1] Abdelmaboud, A. (2021). The internet of drones: Requirements, taxonomy, recent advances, and challenges of research trends. *Sensors*, *21*(17), 5718. https://doi.org/10.3390/s21175718

[2] Ahmad, T., Morel, A., Cheng, N., Palaniappan, K., Calyam, P., Sun, K., & Pan, J. (2025). Future UAV/Drone Systems for Intelligent Active Surveillance and Monitoring. *ACM Computing Surveys*, *58*(2), 1-37. https://doi.org/10.1145/3760389

[3] Ali Shah, S. A., Fernando, X., & Kashef, R. (2024). A survey on artificial-intelligence-based internet of vehicles utilizing unmanned aerial vehicles. *Drones*, *8*(8), 353. https://doi.org/10.3390/drones8080353

[4] Ashraf, S. N., Manickam, S., Zia, S. S., Abro, A. A., Obaidat, M., Uddin, M., ... & Alsaqour, R. (2023). IoT empowered smart cybersecurity framework for intrusion detection in internet of drones. *Scientific reports*, *13*(1), 18422.

[5] Bhargavi, M. S., Hemavathi, P., Jaganath, C., & Narendra, K. (2025). Unlocking the Potential of Machine Learning for Enhanced Security in Drone-Enabled IoT Networks. In *Machine Learning for Drone-Enabled IoT Networks: Opportunities, Developments, and Trends* (pp. 107-120). Cham: Springer Nature Switzerland.

[6] Biswas, D., Dubey, A., & Gulati, M. (2025). Deep ocean exploration and marine data acquisition: Uses of autonomous underwater vehicles (AUVs). *International Journal of Aquatic Research and Environmental Studies, 5*(1), 501–509. https://doi.org/10.70102/IJARES/V5I1/5-1-46.

[7] Bithas, P. S., Michailidis, E. T., Nomikos, N., Vouyioukas, D., & Kanatas, A. G. (2019). A survey on machine-learning techniques for UAV-based communications. *Sensors*, *19*(23), 5170. https://doi.org/10.3390/s19235170

[8] Cheng, N., Wu, S., Wang, X., Yin, Z., Li, C., Chen, W., & Chen, F. (2023). AI for UAV-assisted IoT applications: A comprehensive review. *IEEE Internet of Things Journal*, *10*(16), 14438-14461.

[9] Divakar, D., Kanmani, & Supriya, A. V. (2025). Drone Swarm Coordination Using Machine Learning in IoT Networks. In *Machine Learning for Drone-Enabled IoT Networks: Opportunities, Developments, and Trends* (pp. 39-64). Cham: Springer Nature Switzerland.

[10] Dutt, S., Thakur, R., Kandwal, A., Kumar, P., Jasrotia, R., Lakshmaiya, N., ... & Chan, C. K. (2025). Emerging EM wave sensors for non-invasive glucose monitoring: Review, techniques and developments. *Sensors and Actuators Reports*, *9*, 100282. https://doi.org/10.1016/j.snr.2025.100282

[11] Gholami, A. (2024). *Autonomous UAV networks based on artificial intelligence*. *International Journal of Research Publication and Reviews, 5*(4), 6709–6723.

[12] Gu, X., & Zhang, G. (2023). A survey on UAV-assisted wireless communications: Recent advances and future trends. *Computer Communications*, *208*, 44-78.

[13] Haider, S. A., Zikria, Y. B., Garg, S., Ahmad, S., Hassan, M. M., & AlQahtani, S. A. (2022). AI-based energy-efficient UAV-assisted IoT data collection with integrated trajectory and resource optimization. *IEEE Wireless Communications*, *29*(6), 30-36. https://doi.org/10.1109/MWC.001.2200105

[14] Hashima, S., Gendia, A., Hatano, K., Muta, O., Nada, M. S., & Mohamed, E. M. (2025). Next-gen uav-satellite communications: Ai innovations and future prospects. *IEEE Open Journal of Vehicular Technology*.

[15] Hassan, J., Khalifa, S., & Misra, P. (Eds.). (2025). *Machine Learning for Drone-Enabled IoT Networks: Opportunities, Developments, and Trends*. Springer Nature. https://doi.org/10.1007/978-3-031-80961-3

[16] Heidari, A., Jafari Navimipour, N., Unal, M., & Zhang, G. (2023). Machine learning applications in internet-of-drones: Systematic review, recent deployments, and open issues. *ACM Computing Surveys*, *55*(12), 1-45. https://doi.org/10.1145/3571728

[17] Himanshi, Lal, B., Verma, A., Suman, Ahmed, J., Singh, A., ... & Kandwal, A. (2025). Insights into the photocatalytic removal of malachite green organic pollutant by highly efficient hard responsive Ba1− xCoxDyyFe12− yO19 catalysts. *Scientific Reports*, *15*(1), 1225.

[18] Islam, S., Karam, A., Boualem, A., Pathan, K. V., Sayed, A. F., & Rahman, A. U. (2024, May). 6G-Enabled Network Security in Drone Technology: Revolutionizing Communications and Enhancing Security Applications. In *Nordic e-Infrastructure Collaboration Conference* (pp. 28-44). Cham: Springer Nature Switzerland.

[19] Khan, S., Mazhar, T., Shahzad, T., Khan, M. A., Guizani, S., & Hamam, H. (2024). Future of sustainable farming: exploring opportunities and overcoming barriers in drone-IoT integration. *Discover Sustainability*, *5*(1), 470.

[20] Nawaz, M., & Babar, M. I. K. (2025). IoT and AI for smart agriculture in resource-constrained environments: challenges, opportunities and solutions. *Discover internet of things*, *5*(1), 24.

[21] Pal, O. K., Shovon, M. S. H., Mridha, M. F., & Shin, J. (2024). In-depth review of AI-enabled unmanned aerial vehicles: trends, vision, and challenges. *Discover Artificial Intelligence*, *4*(1), 97.

[22] Pandey, T., & Kumar, T. (2021). Swarm intelligence for smart homes activity prediction and algorithm trading. *International Academic Journal of Science and Engineering, 8*(4), 39–43. https://doi.org/10.71086/IAJSE/V8I4/IAJSE0830

[23] Prakash, M., & Prakash, A. (2023). Cluster Head Selection and Secured Routing Using Glowworm Swarm Algorithm and Hybrid Security Algorithm for Over IoT-WSNs. *International Academic Journal of Innovative Research*, *10*(2), 01-09.

[24] Rashid, A. B., Kausik, A. K., Khandoker, A., & Siddque, S. N. (2025). Integration of Artificial Intelligence and IoT with UAVs for Precision Agriculture. *Hybrid Advances*, 100458.

[25] Rezvani, A., Mirzaei, A., Mikaeilvand, N., Nouri-Moghaddam, B., & Gudakahriz, S. J. (2025). A novel framework for enhancing data collection macro-strategies in heterogeneous IoT networks using advanced mathematical modeling. *Archives for Technical Sciences, 2*(33), 1–21. https://doi.org/10.70102/afts.2025.1833.001.

[26] Sapkota, R., Roumeliotis, K. I., & Karkee, M. (2025). UAVs Meet Agentic AI: A Multidomain Survey of Autonomous Aerial Intelligence and Agentic UAVs. *arXiv preprint arXiv:2506.08045*.
[27] Sarkar, N. I., & Gul, S. (2023). Artificial intelligence-based autonomous UAV networks: A survey. *Drones*, *7*(5), 322. https://doi.org/10.3390/drones7050322
[28] Seid, A. M., *et al.* (2025). Reliable and efficient data collection in UAV-based IoT networks. *IEEE Internet of Things Magazine, 8*(1), 64–71.
[29] Shaikh, M. S., Mungale, S., Agrawal, N., Khodifad, N., & Shaikh, M. I. (2025, April). The Convergence of UAVs, IoT, and Edge Computing: A New Era of Data-Driven Precision Farming. In *2025 International Conference on Data Science and Business Systems (ICDSBS)* (pp. 1-7). IEEE. https://doi.org/10.1109/ICDSBS63635.2025.11031867
[30] Sharif, S., Zeadally, S., & Ejaz, W. (2024). Resource optimization in UAV-assisted IoT networks: The role of generative AI. IEEE Internet of Things Magazine.
[31] Sikarwar, T. S., Chauhan, A. S., Jain, N., & Mathur, H. (2025). Application of predictive analytics in IoT data processing. *Indian Journal of Information Sources and Services, 15*(2), 340–348. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.42
[32] Veerappan, S., & Arvinth, N. (2025). IoT-Enabled Communication Network for Real-Time Disease Alerts in Smart Aquaculture Systems. *Journal of Intelligent Assistive Communication Technologies*, 1-7. https://doi.org/10.17051/JIACT/01.02.01
[33] Wan, F., Yaseen, M. B., Riaz, M. B., Shafiq, A., Thakur, A., & Rahman, M. O. (2024). Advancements and challenges in UAV-based communication networks: A comprehensive scholarly analysis. *Results in Engineering*, *24*, 103271.
[34] Zhang, Q., Furqan, M. D., Nutzhat, T., Machida, F., & Andrade, E. (2025). Dependability of UAV-Based Networks and Computing Systems: A Survey. *arXiv preprint arXiv:2506.16786*.
[35] Zhou, L., Yin, H., Zhao, H., Wei, J., Hu, D., & Leung, V. C. M. (2024). A comprehensive survey of artificial intelligence applications in UAV-enabled wireless networks. *Digital Communications and Networks*. https://doi.org/10.1016/j.dcan.2024.11.005

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