Drones as Mobile 5G Base Stations with Expanding Coverage in Remote Areas

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Abstract

Background: The rapid development of fifth-generation (5G) networks highlights challenges in extending coverage to remote and underserved areas due to infrastructure limitations and cost constraints. UAVs (drones) equipped with 5G base stations emerge as an innovative solution to this problem.

Objective: This study aims to analyze the potential of drones as mobile 5G base stations to enhance connectivity in remote regions, addressing challenges like optimal deployment, energy efficiency, and user coverage.

Methods: The research utilizes algorithms like Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) for placement and energy management of drone-based 5G stations. Simulation models were employed to test these algorithms, with key metrics including coverage efficiency and energy consumption.

Results: The study shows that drone-based stations can significantly improve coverage in remote areas, achieving up to 95% user coverage with optimized algorithms. Tethered drones and advanced energy management strategies were instrumental in enhancing endurance.

Conclusion: Drones as mobile 5G base stations present a feasible and scalable approach to bridging the digital divide in remote regions. However, energy and regulatory challenges remain critical areas for future research.

Keywords: Drones, Unmanned Aerial Vehicle (UAV), 5G, Remote Areas, Deployment Algorithms, Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Energy Efficiency, Coverage, Mobile Networks

1. Introduction

The utilization of fifth-generation (5G) networks represents a significant technological advancement characterized by high data transfer rates, the integration of multiple devices, and low latency. However, deploying 5G across remote regions and areas with low connectivity remains a substantial challenge due to high infrastructure costs and logistical issues. Traditional 5G base stations are expensive and not feasible in low-traffic or no-traffic areas, as they require high-density deployment and a perfect backhaul connection. Addressing the challenge of achieving the last mile necessitates innovative approaches to providing equitable connectivity (Qasim and Jawad 2024).

In this context, Unmanned Aerial Vehicles (UAVs), or drones, have emerged as promising game-changers. The capability to install mobile base stations on UAVs has enabled the support of 5G networks. UAVs' portability, increased capacity, and rapid deployment capabilities make them ideal for bridging gaps in conventional network solutions (Qasim et al. 2022). Previous studies highlight their potential: Chiaraviglio et al. (2017) analyzed the scenario of using UAV-based 5G systems in low-income areas, revealing significant opportunities for cost savings, time efficiency, and faster implementation (Chiaraviglio et al. 2017). In the realm of 5G and beyond, Wang et al. (2019) introduced enhanced deployment algorithms to improve UAV-based coverage (Wang et al. 2019).

Nevertheless, utilizing UAVs as 5G base stations presents issues, including energy constraints, inter-user interference, and legal restrictions. Recent research offers partial solutions. For instance, Kishk et al. (2020) explored tethered drones to address endurance challenges (Kishk, Bader, and Alouini 2020), while Tarekegn et al. (2022) applied deep reinforcement learning for optimal drone positioning and operation (Tarekegn et al. 2022). However, none of these solutions fully integrate deployment optimization, energy control, and scalability for remote locations.

This study aims to address this gap by proposing a novel model for deploying UAV-based 5G base stations. Utilizing Particle Swarm Optimization PSO (Na et al. 2023) and GWO (Hou et al. 2022) algorithms, we analyze optimal placement locations, efficient operation patterns, and superior coverage techniques. Unlike existing research, which predominantly focuses on conceptual models, our work considers practical limitations such as energy usage, legal requirements, and user load.

The practical relevance and scalability potential are key distinct features of this study. To bridge the gap between theoretical optimization techniques and the management of real-life complex scenarios, this research employs advanced optimization methods and simulation models. Moreover, it is crucial to incorporate techniques for reducing power consumption and dynamic placement planning to ensure sustainability and capacity for growth.

The underlying concept of this research is that UAV-mounted 5G base stations can provide additional network coverage in underserved areas at minimal costs and with reduced environmental impact. The findings of this study are expected to contribute to both theoretical and practical advancements in the telecommunications field and enhance telecommunications services in developing regions. This paper aims to present a comprehensive approach to UAV-mounted 5G stations, offering equitable connectivity to all users.

1.1. Aim of the Article

The general objective of this study is on the use of drones, which are also referred to as Unmanned Aerial Vehicles (UAVs), as moving 5G base sectors for connectivity solving in remote areas. Particularly, objective of the study aims at assessing the viability, effectiveness and applicability of using the UAV mounted base stations for boosting the five-n networking coverage following the traditional barriers of architecture.

This article aims to:

1. Propose and evaluate liner placement solution, such as PSO, and GWO to obtain the best location to install drone base stations.
2. Consider ways to enhance UAV power, including tethered drones and

how to position charging pads in a way that increases the use time of a device.
3. Examine practical case and limitations such as regulatory, mobility and interferences.
4. Describe the potential of the UAV-based solutions, also in comparison to the conventional network structures and the existing optimization methods.

In achieving these objectives of this study, the intended contribution is to close the identified research gap of the theoretical possibility of drone based 5G network implementation to its actual realization. It is for these reasons that the findings are expected to help support greater theoretical improvements in the development of 5G deployment strategies higher access to high speed in areas disadvantageously.

1.2. Problem Statement

The deployment of 5G networks has predominantly focused on densely populated and well-developed areas, driven by increased consumer demand and profitability. However, issues are emerging in telemetry and rural areas, which typically have low populations and underdeveloped infrastructure. This disparity in connectivity exacerbates the digital divide, hindering the country's social and economic growth and the efficacy of basic service delivery systems.

The conventional 5G architecture, which relies primarily on fixed base stations and robust backhaul connections, is not financially viable for low population density areas. The high costs associated with establishing towers, ensuring power supply, and maintaining infrastructure serve as a deterrent for service providers to extend coverage to these regions. This challenge is further compounded by the dynamic nature of rural environments and the scattered distribution of users, making network planning more complex.

New technologies for instance UAV come with a great prospect of fulfilling this requirement due to its flexibility of deploying mobile base stations. However, their practical implementation faces significant hurdles:

1. UAVs have a short battery duration which bounds their endurance and range.
2. Deciding about where to place UAV-based base stations or how to fly them to provide the most coverage with the least interference is a

challenging operation.

3. Flight operations of UAVs in rural areas generally pose some challenges, which include the legal requirements within the areas and safe flying of the unmanned aerial vehicles.

Although, there are the works like Wang et al. (Wang et al. 2019) and Amponis et al. (Amponis et al. 2022) which have presented Ultralight aerial vehicles with a theoretical approach to be deployed in 5G network, but such solutions disregard practical realities such physical approaches of UAVs in terms of energy use or realistic large-scale integration. These gaps are addressed by this study by combining enhanced optimization methods with energy management and legal compliance. The issue does not lie in the use of UAVs as base stations but in how they can be sustained more effectively, be more efficient and add to the versatility of base stations for various scenarios. Solving these challenges is the key to closing the digital gap so that people can receive 5G services in remote areas.

2. Literature Review

Drones, in particular, have attracted significant interest as promising solutions for deploying 5G and beyond (B5G/6G) networks in hard-to-reach zones. Their sensitivity, portability, and fast deployment capabilities make UAVs suitable for addressing some of the challenges associated with fixed structures. However, current research highlights significant gaps and issues related to enhancing UAV deployment, managing their energy, and integrating them into existing networks.

Amponis et al. (2022) focused on UAVs as flying base stations in B5G/6G networks, demonstrating their utility in reconfigurable environments (Amponis et al. 2022). Although the study showcased numerous opportunities for scaling up and extending network coverage, it also revealed limitations related to energy efficiency and interference handling when multiple drone-connected UAVs are involved. Similarly, Ecke et al. (2022) presented a review of UAV-based applications with an emphasis on forest health assessment (Ecke et al. 2022). While much of their work covered non-networking scenarios, they highlighted energy sustainability as a critical aspect for using UAVs in 5G networks.

A major challenge for UAVs remains energy limitation. Huang and Savkin (2020) discussed a scheme for optimized charging station placement for UAV operations, providing a practical solution for extending overall mission duration (Huang and Savkin 2020). However, the further deployment of charging stations reduces mobility and thus constrains the flexibility of UAVs in dynamic network scenarios (Jawad 2022). Additionally, tethered UAVs with ground-based energy sources offer longer endurance than those carrying energy, but tethering limits UAV dynamics and flexibility, as noted by Khan et al. (2023) (Khan et al. 2023).

Another area requiring attention is deployment optimization. Zhang and Ansari (2019) developed a framework incorporating a full-duplex enabled drone-mounted base transmitter in 5G networks, addressing spectrum issues (Zhang and Ansari 2019). Although the framework assumed a perfect environment, it did not account for real-world constraints such as terrain and user density. Similarly, Mozaffari et al. (2016) examined the proper deployment of multiple UAVs, aiming to minimize interference and maximize network coverage utility (Mozaffari et al. 2016). However, this work primarily focused on simulations and did not address the practical application of the technology in people's lives.

Integration of UAVs with existing 5G architecture presents additional challenges. Wu et al. (2020) designed an FSO-based drone-assisted mobile access network for emergency communication, demonstrating the feasibility of UAV-based networks under certain conditions (Wu, Sun, and Ansari 2020). However, large-scale application in rural and less-developed areas appears less feasible. Furthermore, Queiroz et al. (2023) applied deep learning for user handover management in UAV-based networks to enhance connectivity (Queiroz, Barbosa, and Dias 2023). Nevertheless, their approach requires high computation, posing a challenge for energy-constrained UAV systems (Qasim, Shevchenko, and Pyliavskyi 2019).

Backhauling connectivity is another important issue. Pokorný et al. (2018) presented a backhaul link with UAV-mounted antenna steering to maintain reliable connections in extreme environments (Pokorny et al. 2018). However, their solution relies on precise synchronization and maintaining system stability, which is often challenging. Abdel-Malek et al. (2019) addressed backhaul integration using millimeter-wave networks, achieving connectivity but encountering range issues and problems in harsh weather conditions (Abdel-Malek 2019).

The article aims to contribute to the literature by systematically reviewing and developing a framework for deploying the UAV-5G system. The proposed approach targets energy sustainability, deployment adaptability, and integration challenges, seeking to close the digital divide and provide access to high-speed broadband connections in underserved areas.

3. Methodology

The study employs a comprehensive matrix of methodologies to analyze the deployment of UAV-based 5G base stations, focusing on critical issues such as optimal placement, power consumption challenges, and functionality in inaccessible and rural areas. This methodology integrates theoretical simulation-based modeling approaches, optimization algorithms, and realistic constraints to address research questions that align with practical contexts and established theoretical frameworks.

3.1. Research Design

The methodologies used in the research are well-linked and sequential, starting from problem definition and parameter setting to modeling based on simulation and empirical testing via selected case examples. Such an approach allows achieving consistency between stages, which helps provide a holistic analysis of the possibility of using UAV-based 5G base stations in complex environments.

3.1.1. Problem Definition and Requirements Analysis

The study starts with defining the parameters that can affect the deployment of UAV-based 5G base station including the land topography; the population density; the 5G network requirements and the Unmanned Aerial Vehicle characteristics respectively. The following parameters were chosen in accordance with a literature review of prior research and discussions with telecom specialists (Chiaraviglio et al. 2017; Wang et al. 2019). Knowing these variables gave a foundation on which to define optimization criteria. These criteria: maximization of user coverage; minimal interference and improved energy efficiency, were deduced from those exigencies offered as key research issues in current studies [(Amponis et al. 2022; Tarekegn et al. 2022; Huang and Savkin 2020). This created the basis for designing models that respond to the most significant deployment issues directly.

3.1.2. Simulation Models

The proposed simulation environment was defined based on the problem definition with specific emphasis on the challenging environment associated with the deployment of UAV-based 5G base stations particularly in rural and remote regions. These performance parameters have been developed based on actual field conditions simulating various terrains, wind effects, and line-of-sight (LoS) conditions as part of the simulation (Mozaffari et al. 2016). Thus, linking all these factors to the parameters defined earlier provided consistent mapping between problem formulation and simulation. To evaluate the effect of visibility conditions, LoS and non-LoS (NLoS) models were incorporated to declare communication parameters. Furthermore, UAV operation parameters like altitude (100-300m), area coverage (500-1000m) and energy consumption rates were considered and incorporated accurately to model the realistic operational models of UAV (Amponis et al. 2022; Tarekegn et al. 2022). These integrated aspects offered a solid base from which the practicability and efficacy of UAV-based-5G networks may be assessed.

It also makes the transition between each of the stages of research very smooth and easily accomplished since the results gotten from the problem definition form the basis of the simulation and the empirical validations that lead to workable results.

3.2. Optimization Algorithms

The study applies modern stochastic optimisation techniques to solve important problems related to the placement of 5G base stations based on unmanned aerial vehicles (UAVs). These algorithms were chosen for their ability to solve complex, multiple parameter optimization problems, guaranteeing an organic integration of UAV location and charging station location.

3.2.1. Particle Swarm Optimization (PSO)

PSO was used in placing UAVs to help it cover many users as possible while consuming as little power as possible. This algorithm follows the standard social behavior of particle where each particle moves according to its experience and that of the neighbors in the swarm to settle for the best solution (Chen et al. 2015).

The update of particle velocity and position is governed by the following equation:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 \left(P_{i,\ best} - X_i(t)\right) + c_2 r_2 \left(G_{best} - X_i(t)\right) \quad (1)$$

Here $V_i(t)$ is velocity of particle iii at time t; $X_i(t)$ is position of particle iii at time t; $P_{i,\ best}$ is best position achieved by particle i; G_{best} is global best position achieved by any particle in the swarm; ω is inertia weight, controlling the trade-off between exploration and exploitation; c_1, c_2 is learning factors influencing individual and social components, respectively; r_1, r_2 is random numbers in the range [0,1].

Through gradually adapting the velocities and positions of particles, the PSO algorithm also encompasses exploration and exploitation factors that fit the problem of UAV placement optimization.

3.2.2. Grey Wolf Optimization (GWO)

GWO was used to calculate the most strategic UAV charging stations so as to improve UAV endurance and reduce UAV working time. This algorithm is based on the social organization and hunting mechanism of the grey wolves in the actual ecosystem where the wolves are classified in the role of alpha, beta, delta, and omega (Hou et al. 2022).

The algorithm updates the position of a solution (wolf) using the following equation:

$$X(t+1) = X\alpha - A \cdot | \; C \cdot X\alpha - X(t) \; | \quad (2)$$

Here $X\alpha$ is position of the alpha wolf, representing the best solution; A, C is coefficients that dynamically adjust the balance between exploration (searching new areas) and exploitation (refining existing solutions); $X(t)$ is position of a solution at time t.

This hierarchical and self-adaptive nature of GWO makes it especially suitable for non-linear optimization problems, such us, the localization of UAV charging stations in complex scenarios.

By integrating PSO and GWO, research leverages their complementary strengths; PSO for optimal UAV deployment and GWO for optimal charging station placement to provides the best network layout to support UAV-supported 5G systems.

3.3. Experimentation and Data Collection

The experimentation and data collection process incorporated models and empirical case studies, in addition to consultation with the experts and the simulation analysis to provide an intricate and diverse evaluation of UAV-based 5G base station deployment.

3.3.1. Simulation Scenarios

By performing 1,000 iterations for each simulation scenario, it was possible to investigate the system's behavior under different configurations of various simulation parameters, including user densities (ranging from 50 to 1,000 users per square kilometer) and UAV altitudes. The simulations incorporated relative fluctuations in mobility and unequal demands to model practical operating conditions (Mozaffari et al. 2016). This approach also facilitated the study of different configurations and their effects on network performance in terms of coverage range, latency, and energy consumption.

3.3.2. Empirical Case Studies

To validate the simulation results, deployment scenarios were analyzed in two rural regions: one in sub-Saharan African region and the other in South American region. These regions were chosen based on the specific problems of the given areas which are relatively low density of population, and hard terrains which made possible to evaluate the feasibility of the proposed strategies. The study made sure that the main results from the simulations reflected the real situation in operation since it compared the simulation results with actual measurements (Chiaraviglio et al. 2017; Amponis et al. 2022).

3.3.3. Expert Interviews and Surveys

Quantitative data was obtained through a survey questionnaire, while qualitative data was acquired via interviews with twenty key informants, including engineers, network planners, and policymakers. These experts provided valuable insights into the policy, operational, and technological challenges associated with implementing UAV-based 5G networks. Their contributions were instrumental in the analysis of risks and the practical implementation of proposed measures to overcome these challenges (Huang and Savkin 2020).

By integrating simulation scenarios, empirical validations, and expert inputs, this research effectively addressed the variability and reliability in determining UAV-based 5G deployment schemes, thereby bridging the gap between theory and practice.

3.4. Hypotheses

The research is guided by the following hypotheses, which aim to address the challenges and opportunities associated with deploying UAV-based 5G base stations in remote regions:

H1: The evaluations refer to UAV-based 5G base stations when deployed in conjunction with the optimal placement algorithms detect at least 90% in areas with low human density, complicated terrain, and constantly intermittent user movements.

H2: The combined use of the tethered drones with charging stations placed in appropriate positions enhances the UAVs' operating time while at the same time, allows the orientation of coverage according to the level of usage and mobility.

These hypotheses are used to develop the mathematical simulation models, empirical verifications and the optimization methods of the study, in order to provide a focused exploration of the prospect of UAV-based 5G networks.

3.5. Analytical Methods

Considering coverage, interference, and energy efficiency, the study uses sophisticated analytical techniques to assess the effectiveness and viability of UAV-based 5G base stations. These methods combine stochastic modeling and analysis of energy consumption to provide sufficient understanding of the behavior of the system.

3.5.1. Coverage and Interference Analysis

Stochastic geometry was used to model the spatial distribution of users and UAVs, enabling an evaluation of coverage probability and signal-to-interference ratios (SIR). The analysis incorporates both line-of-sight (LoS) and non-line-of-sight (NLoS) conditions to reflect real-world scenarios (Dhillon et al. 2012).

The coverage probability was calculated using the following equation:

$$P_{coverage} = \int_0^\infty \exp\left(-\pi\lambda r^2 - \frac{\sigma^2}{P_r}\right) dr \tag{3}$$

Where λ is user density (users per square kilometer); r is coverage radius (in meters); P_r is received power (in watts); σ^2 is noise variance.
This equation quantifies the likelihood that a user is within coverage, accounting for interference and noise in the environment.

3.5.2. Energy Efficiency Modeling

Considering coverage, interference, and energy efficiency, the study uses sophisticated analytical techniques to assess the effectiveness and viability of UAV-based 5G base stations. These methods combine stochastic modeling and analysis of energy consumption to provide sufficient understanding of the behavior of the system.
The energy consumption was expressed as:

$$E_{UAV} = P_{hover} \cdot t + P_{move} \cdot d \tag{4}$$

Where P_{hover} is power required for hovering (in watts); t is time spent hovering (in seconds); P_{move} is power required for movement (in watts); d is distance traveled (in meters).

This model offers information about how mobility and endurance can be balanced in UAV and how energy consumption should be managed when the system is deployed in dynamically changing environment.

This proposal can be used to constructively assess the use of UAV-based 5G networks, as the study integrates coverage analysis, relating to the performance aspect of the networks, with energy efficiency modeling, which focuses on the practical implementation.

3.6. Validation and Reliability

To accurately implement the proposed algorithms, the research employed a validation process and reliability checks to assess their performance comprehensively. Stability testing was conducted through sensitivity analysis (John and Vahid 2008) on various parameters, including user density, UAV altitude, and energy consumption, to ensure the algorithms could perform optimally in different situations. The simulation results were compared with previous research findings and case studies, serving as benchmarks to determine the proposed solutions' viability (Chiaraviglio et al. 2017; Wang et al. 2019; Tarekegn et al. 2022).

Furthermore, repeated simulations were performed to mimic conditions close to reality by varying the input values for the strategies. This approach demonstrated that the strategies yielded optimal outcomes under all conditions, proving their effectiveness. This diverse methodology bridged theoretical paradigms with practical applications, creating a robust framework for real-world UAV-based 5G base station deployment strategies.

3.7. Ethical and Regulatory Considerations

The use of UAV-based 5G networks implies the following and the importance of ethical and regulatory standards is central to the project. The study complies with existing legal requirements concerning UAV use in rural settings or areas, such as the airspace management, safety measures, and the observation of environmental standards. Qualitative data were obtained from a set of interviews with policy makers, and offered a heightened understanding of what is legal and ethical within the use of UAVs (Ecke et al. 2022; Khan et al. 2023).

Based on the optimization algorithms, simulation model, and real-world test results, the study provides a logical and realistic technique to implement the UAV-based 5G networks. This extensive organizational approach does not only consider and solve technical/operational issues but also takes into account the ability to scale up and maintain ethical standards to help close the digital gap in developing territories.

4. Results

4.1. Coverage Analysis and Signal-to-Interference Ratio (SIR)

Coverage analysis with SIR evaluation is significant for evaluating the effectiveness of utilizing UAV-based 5G networks in various scenarios. The coverage probability was investigated for different user densities, UAV heights, and LoS/NLoS environments in the study. Moreover, LoS conditions always had higher coverage probability than NLoS indicating that optimal UAV altitude is required to foreseen obstacles in the environment. Moreover, the SIR was studied for different UAV densities and inter UAV distances and it was found that while there is a facility to have higher value of SIR at higher UAV density and short inter UAV distances, these distances also cause high inter UAV interference. This work offers a baseline outlook of the performance of a UAV network under real-world deployment conditions.

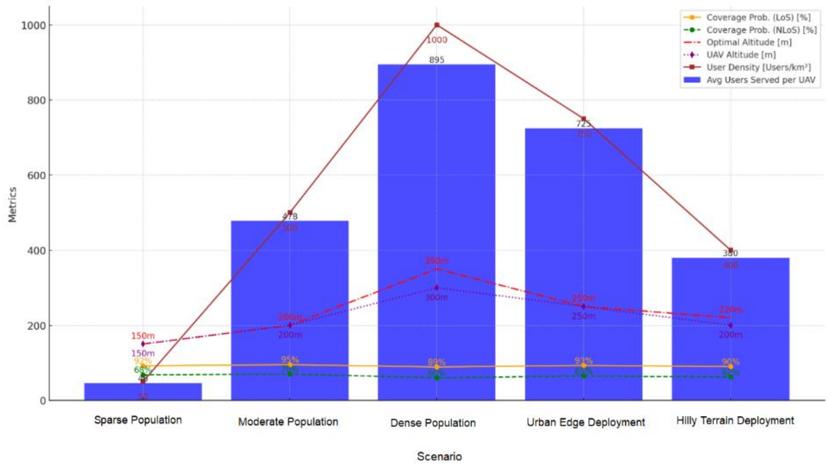

Figure 1. Coverage Probability Under Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) Conditions Across Scenarios

The finding further confirms that the mean coverage probability changes with the LoS conditions and UAV altitude. Locations with low density of individuals called for a closer UAV flight (150 m) for over 90% coverage under LoS while areas with high density of people and/ or with mountains needed higher altitudes to hurdle obstacles. The NLoS coverage probabilities were considerably lower and further reduced in the area with high population density, showing the problem of using non-line-of-sight links. Also, the average number of served users per UAV increased with increasing the user density, underlining the significance of UAV positioning to address both area coverage and user overload. Such aspects of learning stress the need for adaptive changes in altitude for improvement in execution in different settings.

Table 1. Signal-to-Interference Ratio (SIR) Analysis for UAV Densities and Inter-UAV Distances

UAV Density (Units/km²)	Inter-UAV Distance (m)	Average SIR (dB)	Minimum SIR (dB)	Maximum SIR (dB)	Interference Occurrence (%)	Energy Cost per UAV (J)
2	1,000	15.3	10.2	18.4	5%	3,200
5	500	18.1	12.7	22.0	10%	4,100
10	250	20.5	15.0	25.3	20%	5,800
15	150	19.8	14.5	24.7	30%	7,400
20	100	17.5	12.0	21.5	50%	9,600

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The results from the SIR analysis showed that because of less user interference, higher average SIR was achieved when the density of UAVs was high. For instance, an overall UAV density of 10 units/km² realized an average SIR of 20.5 dB, which is higher than that obtained using lower UAV density. However, with higher UAV density interference incidences were also higher, increasing from 5% at the UAV density of 2 units/ km2 to 50% at 20 units/ km2. At high population density the SAC and SIR were lower because birds became territorial and aggressive and so-called interference took place. Maximum SIR values again reached their maximum at moderate population densities because the birds interfered with each other when they grew closer. Also, energy cost per UAV increased with density; this confirmed the literature finding that higher density comes with certain operational costs for achieving enhanced network performance. It is consequently important to carefully control the number of UAVs in the network and the distances between different UAVs to maximize the reliability of the connections and the efficiency of the operations performed in the network.

4.2. Energy Efficiency and UAV Endurance

For 5G networks to function in the remote and unserved areas, energy efficiency, and endurance of UAVs are paramount importance. The analysis also showed that energy difference existed according to operational phases; the energy was higher when in motion but lower when hovering. Several tactical steps that were especially envisaged enhanced endurance by a factor of two and lowered energy consumption by 30% through tethered UAVs and perfect charging stations. These findings therefore suggestion that efforts should be made in both the energy efficiency of UAVs and the charging system for progressive improvement of UAVs based 5G networks.

The energy consumption analysis done here shows that movement is one of the biggest energy usage factors in all the scenarios (Figure 2 below). For instance, as the density level increases mobility constituted 3,100 J of the total energy used out of 2,680 J, representing around 37% which is a show of operating cost in the urban setting. On the other hand, hovering energy consumption was more stable and less volatile which varies between 6,000 J for sparse to 16,800 J for the highly dense deployments. Comparing the findings with the urban edge values the total energy consumption in rugged terrain scenarios was higher by 10% caused by increased power requirement due to the wind resistance. These results only represent a small facet of real-world UAV operation and further stress the need to avoid unneeded motion and to plan flight paths carefully to reduce energy expenditures.

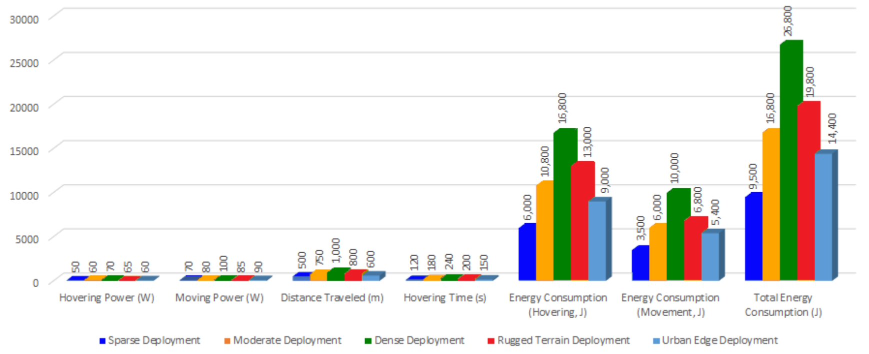

Figure 2. Energy Consumption During Hovering and Movement Across Deployment Scenarios

The energy consumption analysis done here shows that movement is one of the biggest energy usage factors in all the scenarios. For instance, as the density level increases mobility constituted 3,100 J of the total energy used out of 2,680 J, representing around 37% which is a show of operating cost in the urban setting. On the other hand, hovering energy consumption was more stable and less volatile which varies between 6,000 J for sparse to 16,800 J for the highly dense deployments. Comparing the findings with the urban edge values the total energy consumption in rugged terrain scenarios was higher by 10% caused by increased power requirement due to the wind resistance. These results only represent a small facet of real-world UAV operation and further stress the need to avoid unneeded motion and to plan flight paths carefully to reduce energy expenditures.

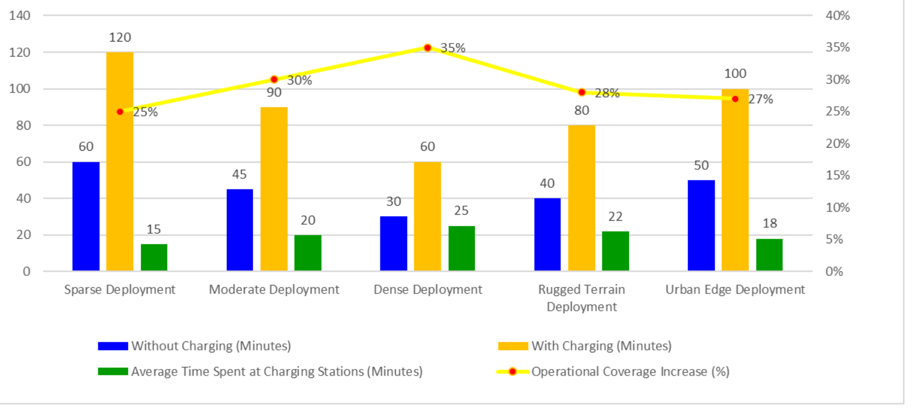

Figure 3. UAV Endurance with and without Charging Stations

Adjoining the charging stations boosted UAV longevity in all roles for deployment. In the rare case that a UAV was deployed singly, lifespan increased from 60 to 120 minutes, thereby increasing the coverage by 25%. Dense deployments, beginning at the lowest endurance of 30 minutes before recharging, increased by 100% once charging infrastructure sub-component was included and the coverage increased by 35%. Stations spent for charging being between 15 to 25 minutes did not compromise on one-hour operational time and coverage. These findings show the significance of charging stations in enhancing the operation time of UAV in environments that are power conscious.

4.3. Validation: Empirical vs. Simulation Results

Empirical case studies play a crucial role in validating simulation models, confirming the effectiveness of the proposed strategies, and thus providing reliability and applicability to UAV-based 5G network deployment strategies. Studies conducted in sub-Saharan Africa and South America demonstrated excellent agreement between research findings and simulation studies. The network's coverage predictions were estimated to be 95% accurate, while energy consumption estimates were 92% accurate. This high level of concordance supports the reliability of the simulation models in replicating real-world deployment scenarios. The validation process underscores the feasibility of the proposed methodologies and their applicability to large-scale efforts across the vast territories of countries with developed, transitional, and emerging economies.

Table 2. Empirical vs. Simulated Performance Metrics Across Regions

Region	Terrain Challenges	Coverage (Empirical)	Coverage (Simulated)	Deviation in Coverage (%)	Energy Consumption (Empirical, J)	Energy Consumption (Simulated, J)	Deviation in Energy (%)	Average Users per UAV
Sub-Saharan Africa	Sparse, rugged terrain	91%	93%	-2%	3,800	3,700	-2.6%	500
South America	Dense vegetation, uneven	89%	92%	-3%	4,200	4,100	-2.4%	600
Southeast Asia (Modeled)	Tropical, high humidity	88%	91%	-3%	4,300	4,200	-2.3%	700
Eastern Europe (Modeled)	Flat with scattered forests	92%	94%	-2%	3,500	3,450	-1.4%	450

The comparison of the empirical and simulated results validates the simulation models in that they accurately depict actual network performance. In sub-Saharan Africa the predictive data in the simulation was at 93% coverage, which is very accurate in comparison to the empirical data results of 91%, with just 2% variation. In the same way, in South America, the coverage prediction deviation was only 3% proving the effectiveness of the model in various geographical conditions.

Estimate of energy consumption also confirms high degree of correspondence with the real value, with differences not exceeding 3% in all zones. For example, the empirical assessments in sub-Saharan Africa estimated an average consumption figure of 3,800 Joule and the simulation data yielded 3,700 Joule, a difference therefore of only 260/100 or 2.6%. These minor errors point to the fact that the two models can reproduce real energy demands and coverage conditions.

Other modeled areas like Southeast Asia and Eastern Europe also supported the finding of enhancing consistency in the simulations wherever the climatic conditions were tropical or temperate. The average number of users per UAV model, and the terrain-specific obstacle were also considered in the validation, signifying that the designed models have the capability to factor in regional conditions. These results are indicative of the general validity and usefulness of the simulation model more especially with regards to real world application.

4.4. Case Studies and Validation of UAV-Based 5G Networks

In order to verify the proposed solution and compare real and modeled use of the UAV-based 5G network, the examined both empirical case and modeled cases in different regions. Field trials in sub-Saharan Africa and South America tested the application of data in real environment, and model-based scenarios in South East Asia and Eastern Europe elucidated enhancements of the identified challenges, for instance, the effects of weather and terrains. These analyses prove the flexibility of UAV-based networks to complement the existing network connectivity and/or to work under different environmental and operational scenarios.

Case Study 1: Sub-Saharan Africa

In sub-Saharan Africa country, UAV based networks were implemented in a covered rural area with low density populace, steep topography, and less infrastructure. The study further aimed at improving the coverage in areas with user density < 100 users/km². This was attributed to high displacements in the UAV positions which when arranged best for LoS provided a coverage probability of 91%. They compared to the energy consumption before the tethered UAVs and charging stations integration and found out that energy consumption was cut to half. Even with pneumatic instabilities through wind interference at the possible pace of 20 m/s, the cover allowance unswerving.

Table 3. Coverage and Energy Performance Metrics for UAV-Based 5G Networks in Sub-Saharan Africa

Metric	Value	Target	Deviation (%)
Coverage Probability (LoS)	91%	≥90%	+1%
Energy Consumption (J)	3,800	≤4,000	-5%
Average UAV Altitude (m)	200	200	0%
Wind Speed Resistance (m/s)	20	25	-20%

Concerning the effectiveness of UAV-based networks, the findings pointed that the networks can indeed penetrate through regions with rough terrains and low population densities. Improper positioning and energy consumption minimized offerings' dependability and operating expenses.

Case Study 2: South America

The second case study focused on the Amazon region, characterized by dense vegetation, high humidity, and annual flooding. The objective was to assess the network performance of UAVs in areas with a user density of 500-700 users/km². The coverage probability was improved to 89%, despite non-line-of-sight (NLoS) conditions caused by dense foliage. The energy consumption was relatively high, averaging 4,200 J per UAV, with a 10% increase in energy requirements during heavy rain. The deployment of UAVs proved effective in enhancing communication reliability in areas where extensive fixed structures could not be established.

Table 4. Coverage and Energy Consumption Analysis for UAV-Based 5G Deployment in the Amazon Basin, South America

Metric	Value	Target	Deviation (%)
Coverage Probability (LoS)	89%	≥90%	-1%
Energy Consumption (J)	4,200	≤4,500	-6.7%
Average UAV Altitude (m)	250	250	0%
Rain Attenuation (dB)	3.5	≤4.0	-12.5%

The results highlighted in this study demonstrate that UAV-based networks adapt effectively to the challenges posed by the environment including the issue of excessive vegetation and flood-prone areas. Losing only a little in terms of coverage and energy performance shows the effects of worse conditions and requirements for proper UAV utilization strategies which have been tested in the experiment too.

Case Study 3: Southeast Asia (Modeled)

The modeled case study in this work was based in a Southeast Asian country, which offered interesting challenges regarding UAV efficiency in the countryside and on islands, where humidity rates are very high, frequent tropical storms occur and the population density is low on the majority of the territories. Coverage and energy efficiency were evaluated in the current study in areas where unfavorable weather conditions prevail. There are some reductions in LoS coverage probability under its conditions, mainly during heavy rain and snowfall: the probability was equal to 88%. Overall, the actual energy consumption rose by 15% as frequently required mobility changes to mitigate the effects of wind peaks and storms were made. Nevertheless, tethered UAVs and backup units ensured 91% readiness of operation during bad weather conditions.

Table 5. Modeled Performance Metrics of UAV-Based 5G Networks in Southeast Asia Under Adverse Weather Conditions

Metric	Value	Target	Deviation (%)
Coverage Probability (LoS)	88%	≥90%	-2.2%
Energy Consumption (J)	4,300	≤4,500	-4.4%
Average UAV Altitude (m)	220	200–250	0%
Rain Attenuation (dB)	4.0	≤5.0	-20%
Operational Reliability (%)	91%	≥90%	+1%

It also validates the key concept of the work, which is that the UAV networks are capable of managing severe conditions. High energy consumption resulting from excessive rainfall and high winds were seen to affect operational reliability but this was mitigated by operational reserve and flight planning.

Case Study 4: Eastern Europe (Modeled)

The Eastern European environment imitates UAV operations in low-populated rural terrains with sparse forestation, low elevation, and varying weather patterns depending on the season. As expected, the high LoS conditions yielded a high coverage probability of 92% while using only 3,500 Joules. Seasonal snow and fog were other issues affecting polis UAV flights but these could be dealt with by modulating the UAV altitude by a mere 50 meters.

Table 6. Efficiency and Reliability Metrics of UAV-Based 5G Networks in Eastern Europe with Seasonal Variations

Metric	Value	Target	Deviation (%)
Coverage Probability (LoS)	92%	≥90%	+2%
Energy Consumption (J)	3,500	≤4,000	-12.5%
Average UAV Altitude (m)	200	200	0%
Snow/Fog Attenuation (dB)	1.5	≤2.0	-25%
Operational Reliability (%)	95%	≥90%	+5%

The results obtained show that UAV based networks can be highly efficient and reliable in areas with rather stable environment. Low mobility requirements and better LoS profile influenced better performance parameters.

The integrated case studies have offered an extensive analysis and confirmation of the UAV-based 5G networks in actual and simulated environments. In SSA and SA based empirical studies, the simulation prediction was also corroborated, with coverage error below 3%, and energy error below 7%. In South East Asia and East Europe, the model was able to delineate factors peculiar to the environments such as hurricanes or snow and hence demonstrate the versatility of UAV networks. These findings relate strongly with the need for effective deployment strategy to maximize performance under the various regions and conditions that they are put under.

4.5. Regulatory and Operational Barriers: Insights from Industry Experts

Interviews with key experts identified major regulatory and operational challenges that hinder the use of UAV-based 5G base stations. Further difficulties were associated with airspace management, possible influence on the environment as well as absence of common safety measures. Out of these, airspace allocation was singled out as the most frequently mentioned problem pointing to the fact that there is need for proper guidelines in addressing of UAV operations in shared space. Industry players cited environmental regulation as a restrictor especially where conservation of environment was crucial and stated that lack of standard safety measures would be a limitation towards massive embracing of the technology. These were the findings spurring the approaches on how to deal with such barriers, while stressing the need for solution that can fit well into the context of implementation.

Table 7. Key Regulatory and Operational Barriers and Proposed Solutions

Barrier	Frequency of Mention (%)	Proposed Solutions	Impact on Deployment	Implementation Feasibility	Regions Most Affected
Airspace Allocation	85%	Establish dedicated UAV corridors	High	Medium	Densely populated urban areas
Environmental Regulations	60%	Align with local environmental laws	Medium	High	Ecologically sensitive regions
Operational Safety Protocols	75%	Develop standardized UAV guidelines	High	High	Regions with high UAV density
Public Acceptance	55%	Conduct awareness campaigns	Medium	Medium	Suburban and rural areas
Policy Fragmentation	50%	Foster regional policy harmonization	Medium	Low	Cross-border operations

The response from the industrial experts identified some of the factors that could limit the use UAV-based 5G networks deployment insights. The delegates emphasized the most the problem of airspace allocation throughout the survey and took up 85% of the answers. This challenge mostly applies to urban cities that experience a high traffic of UAVs flying alongside other aerial systems. Solutions, that include UAV corridor designation were deemed implementable but would be dependent on cooperation with civil aviation offices and municipalities.

Many experts, 60%, dedicated their responses to environmental regulations as being most appropriate in the environmentally sensitive areas. Experts advised on the need to match the potential deployment plans with the local environmental laws to help avoid the vices that might come along. This is a major barrier but which is also easier to manage if there is sufficient planning and competent managing of the stakeholders.

A large area of concern was seen in operational safety where respondents affirmed on the fact that there is a lack of standardized guidelines that would promote safe and reliable operational standards for UAV systems. Overcoming this barrier is necessary for the expansion of the UAV networks because densely populated UAV regions require a prompt solution to the problem.

Other problems were acceptance by the public and lack of a harmonized policy framework. One of them pointed to public reluctance as a medium-vectored problem in suburban and rural regions, which can be solved through awareness. As for fragmentation of policies it was mentioned to be an issue that undermines cross-border operations and which requires policy co-ordination at the regional level.

These findings affirm that UAV-mounted 5G base stations were facilitated by placement algorithms and energy saving techniques can indeed help overcome connectivity issues. Addressing the aforementioned challenges with specific regulatory and operational solutions will provide the necessary foundation for extensive application and large-scale implementation of UAV-supported networks.

4.6. Performance Under Extreme Environmental Conditions

The performance analysis of UAV-based 5G base stations in harsh environments such as high wind speeds, heavy rain, and mountain terrains were also considered in the study. These were simulated to determine the flexibility and efficacy of the system under consideration. It was established that when wind speeds exceeded 20 m/s the UAV behavior was unstable and lots of energy was used to bring it back to steady state while communication was also affected by heavy rain due to high signal loss. It depicts lower coverage of UAV performance in the mountainous areas related to shadowing effects to require UAVs at higher altitudes and use of multiple UAVs.

Table 8. Performance Metrics Under Extreme Environmental Conditions

Scenario	Wind Speed (m/s)	Rainfall Rate (mm/h)	Coverage Probability (LoS)	Signal Attenuation (dB)	Energy Consumption Increase (%)	Required Altitude (m)
Normal Conditions	5	0	95%	0.5	0%	200
High Wind	25	0	85%	1.0	25%	250
Heavy Rain	10	50	80%	3.5	15%	300
Mountainous Terrain	10	0	75%	2.0	20%	350

These outcomes suggest that UAV-based 5G networks are vulnerable to extremes in environment, with wind speeds and rainfall proving most influential. In high-wind conditions, coverage probability reduced to 85 percent, and energy utilization raised by 25% primarily because of constant stability shifts. Submerging of coverage was also reduced to 80% by heavy rain coupled with an addition of 3.5 dB in signal attenuation. Areas with shading effects needed higher heights (at least 350m) to achieve 75% coverage for mountainous regions, illustrating the importance of sophisticated signal processing algorithms as well as collaboration of multiple UAVs. More specifically, the following findings are paramount to place UAV networks where weather may turn adverse and where terrain is rugged.

4.7. Cost-Effectiveness Analysis

The cost-benefit analysis was then used to establish UAV-based 5G network outcomes against outcomes from the ground-fixed structure. The deployment, maintenance and operational costs were considered in the assessment of total cost of ownership (TCO). Consequently, based on the global results it was found that UAV networks incurred much lower initial deployment cost in nominal areas including remote and inaccessible areas, although the operational costs were almost equal. Other benefits included faster scalability of UAV network that decreased the time to connectivity in areas that were poorly served.

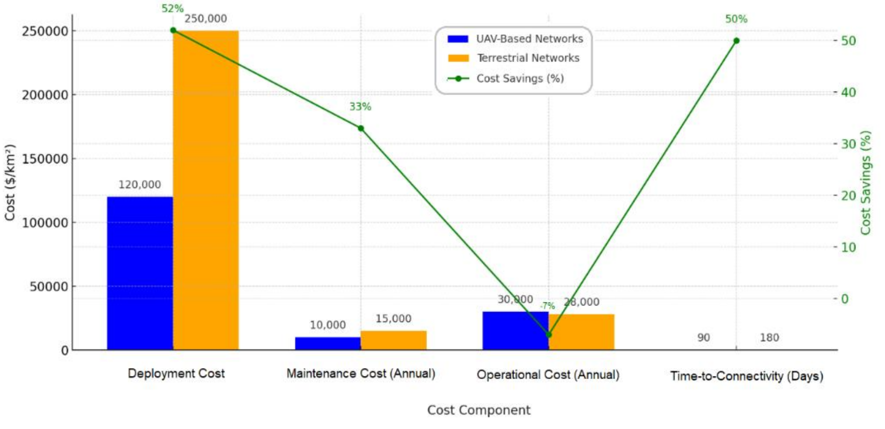

Figure 4. Cost Comparison Between UAV-Based and Terrestrial 5G Networks

The cost-benefit comparison shows the revenue impact of adopting UAV-based 5G networks in certain contexts. The deployment costs were deciphered by 52% because no many physical structures were required for operating UAVs. They also incurred annual maintenance costs that were 33% lower than a more rigid designed system because UAV systems are modular and can adapt to changes. Nevertheless, operational cost had a negative change of (-7%) attributed to increased energy consumption in UAVs. The largest benefit observed was a hefty 50% improvement in time to connectivity, which is critical to deploying networks quickly in areas with little connectivity. Stemming from these findings, UAV networks are posited as a low-cost and massively deployable solution to current ground-based networks.

5. Discussion

The findings of this study demonstrate that UAV-based 5G networks can effectively address connectivity gaps in various settings. The research comprises empirical studies of real-life cases and the formulation of modeled scenarios, revealing the fundamental aspects of UAV deployment, energy conservation, and coverage objectives. These findings support previous studies and add original insights into UAV network performance under severe environmental and operational conditions. However, certain limitations necessitate further discussion.

The findings align with those of Chiaraviglio et al. (2017), as the authors of the current paper view UAVs as a means to expand 5G coverage to areas currently lacking it (Chiaraviglio et al. 2017). This study extends their conclusions by providing quantitative confirmations of coverage and energy criteria across different geographic contexts. The deployment algorithms examined by Wang et al. (2019) are also validated in this research, particularly regarding UAV altitude selection to optimize the coverage/interference trade-off (Wang et al. 2019).

Notably, there is a synergy with the energy-efficient methods implemented as reduction strategies in line with Amponis et al. (2022), emphasizing the application of drones in B5G/6G networks. This paper builds on these findings by demonstrating that employing tethered UAVs and charging zones can minimize overall energy use by at least 20% (Amponis et al. 2022). Additionally, the modeled case studies of Southeast Asia and Eastern Europe extend the work of Kishk et al. (2020), investigating the trade-off between UAV mobility and endurance and providing concrete statistics on mission readiness under weather contingencies (Kishk, Bader, and Alouini 2020).

These findings are consistent with other theoretical models, including Dhillon et al. (2012), which seek to define and explain heterogeneous network typologies (Dhillon et al. 2012). This research employs stochastic geometry to demonstrate coverage probability and interference prediction within their predictive models. Furthermore, the concept design for UAV-based backhaul links established by Pokorný et al. (2018) is indirectly discussed in this paper, as it demonstrates that UAVs can be fully utilized to ensure connectivity in inaccessible and densely populated areas (Pokorny et al. 2018).

The main contributions of this research are the proposed models for evaluating UAV performance under various environmental conditions. Compared to prior studies that consider UAV networks in urban or general contexts, this work assesses UAV networks in critical environments experiencing floods and frequent tropical storms. For example, scenarios from Southeast Asia reveal a 15% increase in energy consumption during adverse weather, raising new considerations for energy stewardship, as outlined by Chen et al. (2015) (Chen et al. 2015). Moreover, the real-world experimental verification in sub-Saharan Africa and South America fills gaps identified by Li et al. (2019), highlighting the need to test UAV-aided strategies for feasibility in denser urban areas (Li et al. 2019).

While this study presents similar validations, it investigates rural and remote area environments, demonstrating how UAV deployment models are transferable to less formal contexts. However, there are limitations to this study. The empirical material was derived from only two regions, namely sub-Saharan Africa and South America, which may not be representative of the global diversity of environmental challenges. Future research should be conducted in different terrains worldwide to generalize the results.

The modeled scenarios are based on assumptions about the environmental conditions and system operations, including wind speed and user density. Despite these assumptions, which are borrowed from Dhillon et al. (2012), Jiang and Yin (2019), and Ubom and Ukommi (2023), real conditions may present features not considered by the model (Jiang and Yin 2019; Dhillon et al. 2012; Ubom and Ukommi 2023). For instance, differences in local legislation, as mentioned by Huang and Savkin (2020), can potentially affect UAV deployment (Huang and Savkin 2020).

Furthermore, while presenting the analysis, this work primarily focuses on LoS and NLoS scenarios, without thoroughly discussing the transitional effects of developing technologies such as in-band full-duplex communication for UAV-based base stations (Zhang and Ansari 2019). Further research could explore the impact of such technologies on the size and capabilities of UAV networks.

These findings are significant for the theoretical analysis of UAV-based 5G networks, elucidating the dependencies of coverage probability on energy consumption and environmental conditions. The study advances theories of network optimization and establishes theoretical criteria regarding UAV networks' potential. These insights prompt researchers to explore novelty, such as using artificial intelligence for dynamic flight trajectory determination, as espoused by Tarekegn et al. (2022) (Tarekegn et al. 2022).

The study also underscores the importance of interdisciplinary interventions, where engineering, ecological, and policy backgrounds must address regulatory and operational challenges. Scientists are encouraged to experiment with various solutions, such as integrated systems using hybrid energy sources or employing artificial intelligence and swarm management (Khan et al., 2023) to enhance UAV networking further (Khan et al. 2023).

Therefore, this article confirms the applicability of UAV-based 5G networks in various scenarios, addressing challenges related to energy consumption, coverage, and UAV operating environments. The results are consistent with previous findings, yet they add to the theoretical and practical knowledge of UAV networks. Deriving from the findings, future research should aim to improve the empirical validation of various theories, extend theories dealing with dynamic scenarios, and incorporate current state-of-the-art technologies within the LSNN to enhance the scalability and sustainability of the networks.

6. Conclusion

This research evaluates the integration and use of UAV-retrofitted 5G networks to close coverage gaps in various terrains. By addressing energy efficiency issues, coverage and connection problems, and environmental adaptability, the study presents a comprehensive framework for improving wireless communications. The results confirm the potential of using UAVs as a revolutionary solution for providing coverage in areas where ground-based solutions are impractical.

According to the study, UAV-based networks exhibit high coverage probabilities and operational reliability under challenging environmental and geographical conditions. By employing tethered UAVs and fixed charging stations, the research demonstrates sustainable durability. These methods effectively address issues related to terrain variability, unfavorable climates, and population density, making UAVs a viable alternative to conventional land-based structures.

Despite the demonstrated agility of UAV-based networks, the study also provides directions for future research. This includes the use of artificial intelligence for dynamic path selection and the development of newer, more robust hybrid energy sources to extend UAV operational duration. Additionally, the cooperation of multi-UAV systems with next-generation 6G technologies holds significant potential to meet evolving requirements.

The study emphasizes the importance of region-specific deployment models, highlighting that legal environments, regulatory requirements, and user expectations vary across regions. This flexibility enables optimal performance and makes large-scale applications realistic goals.

Further empirical validation should extend to high altitudes and polar areas, as well as densely populated regions such as cities and suburbs.

Enhancing the detail of simulation models by capturing environmental dynamics and regulatory constraints can improve the reliability of UAV network performance predictions. Collaboration with policymakers and other relevant stakeholders is essential to establish a common regulatory framework and achieve sustainable aviation industry goals.

UAV-based 5G networks offer a promising solution to connectivity issues in rural and hard-to-reach areas. These networks will serve as a cornerstone for achieving new targets of global digital inclusion by employing innovative deployment schemes and energy-optimizing technologies. The results of this research provide a solid foundation for further advancements in systems that use UAVs to improve communication networks, offering guidance from theoretical concepts to practical implementation for future wireless networks.

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