Low-Latency Communication with Drone-Assisted 5G Networks

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Abstract

Background: Unmanned Aerial Vehicles (UAVs) utilizing and active interface with 5G networks has become the new frontier to tackling problems of latency and energy efficiency, interference, and resource management. Although prior researches explained the benefits of UAV integrated networks; overall assessment of various parameters and cases is still scarce.

Objective: The article seeks to assess the performance of UAV integrated 5G network in terms of latency, power, signal quality, task coordination and coverage optimization and to ascertain the efficiency of optimization algorithms in the improvement of the integrated 5G network.

Methods: Emulations were done in MATLAB and NS3 platforms in urban / suburban / emergency call settings. Latency, power consumption, SINR, and completion time were the performance indicator chosen in the paper. Optimization algorithms: Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), and the Multi-Objective Evolutionary Algorithm (MOEA) is evaluated in terms of Convergence time and Solution quality.

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Results: UAV-aided networks showed 36.7% and 29.2 % improvement in latency and energy consumption, while 33.6 % enhancement in SINR. MOEA offered the best results with 98.3% solution quality, and the PSO being the most convergence oriented. Minor deviations between simulation and real results highlight the need for adaptive mechanisms.

Conclusion: The results presented focus on the enough potential of UAV-assisted 5G networks and their potential influence on improving performances in case of different criteria. Further research should focus on successfully implementing and deploying the proposed solutions and broadening the context of study to include 6G technologies.

Keywords: UAVs, 5G networks, latency reduction, energy efficiency, Signal-to-Interference-Plus-Noise Ratio (SINR), optimization algorithms, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), the Multi-Objective Evolutionary Algorithm (MOEA), task scheduling.

1. Introduction

The growing need for fast and dependable communications drives 5G technology development across all generations of networks. These networks enable multiple applications that need URLLC functions such as autonomous cars and immediate remote medical treatment (Feng et al. 2021). Maintaining dependable network service across various challenging locations and accident scenarios remains difficult despite the latest network development challenges. Integrating unmanned aerial vehicles into 5G networks has shown promise to solve current network issues through scalable and efficient communication design (Shahzadi et al. 2021).

Scientists have shown that using unmanned aerial vehicles improves 5G network performance by creating dependable and fast wireless links (Wu et al. 2021; Qasim et al. 2022). Intelligent communication system-enabled UAVs serve as both aerial base stations and relay nodes to boost the capabilities of ground-based networks (Mahmood 2021). These systems offer immediate network availability when regular networks fail to operate. They strengthen network capacity when infrastructure supplies run low [7]. UAV network support for 5G networks fits within 6G development aims because it improves smart communication while saving power and noticing setting conditions [6].

Expert research projects have studied the communication benefits of using UAV technology. In research (Shahzadi et al. 2021), Shahzadi et al. explored how 5G networks can partner with UAVs to do more jobs and help communities. Feng et al. (Feng et al. 2021) studied how UAVs help deliver

URLLC services to new applications and what challenges need to be solved to reach this objective. Recent research shows UAVs take on a major role as foundational networks for future systems.

IRSs integrated into UAV communications systems open new opportunities for UAV-supported networks. Based on their research Mahmoud et al. presented that integrating IoT systems with IRS-supported UAVs creates better network dependability and reduces power use (Qasim and Jawad 2024). Recent investigations by both Wang et al. (Wang et al. 2021) and Masaracchia et al. (Masaracchia et al. 2021) studied how UAVs bring ultra-reliable low-latency connections to 6G networks while presenting detailed views on UAV network structures and future prospects.

Research papers study distinct low-latency network aspects like energy conservation (Yu et al. 2023), deployment strategies (Wang et al. 2021), and IRS usage (Mahmoud et al. 2021) but do not solve the total 5G UAV network latency obstacle (Jawad 2022). The study shows the need to study how different latency reduction methods work together in these systems.

Researchers show how UAV-powered networks can transform operations but studies need to merge latency reduction with energy efficiency and flexible coverage for diverse real-world settings. Current research studies these factors separately which prevents us from understanding UAV low-latency framework design as a whole. Studying how UAV networks work in difficult recovery situations and busy urban environments remains necessary to prove their effectiveness in all operational settings.

This work develops a new method to deliver low-latency communication across drone-supported 5G networks. The proposed system uses top-level UAV placement methods along with advanced resource distribution and communication adjustment techniques to successfully reduce delay while maintaining system stability. The research develops new knowledge about UAV networks and offers useful recommendations for real-life applications.

The study demonstrates that combining advanced UAV deployment methods with improved communication technologies effectively decreases 5G network delays while enhancing both system stability and power efficiency. This research project uses both simulated models and real-world testing to verify its theory. The methodology studies mobile network designs using drones and develops deployment schemes for 5G networks while measuring latency changes under different traffic scenarios. The research uses machine learning approaches to monitor and adjust network operations which boost overall system performance. The paper aims to build and prove an all-inclusive solution for low-latency data delivery through 5G networks assisted by UAV systems. Specific goals include:

1. Analyzing latency reduction mechanisms in UAV-based communication systems.
2. Optimizing UAV deployment strategies to enhance coverage and minimize energy consumption.
3. Developing adaptive communication protocols that respond to network dynamics in real time.
4. Validating the framework through simulations and case studies in diverse operational scenarios.

Through this research the study aims to advance wireless communication expertise while creating networks that efficiently incorporate UAVs as standard technology. The integration of drones with networks will transform how telecommunications work today while paving the way for better disaster response and smart city technology.

1.1. The Aim of the Article

The article examines the added value of utilizing UAVs to enhance 5G network performance by reducing latency, lowering energy consumption, and implementing protective interference control schemes. Traditional 5G networks struggle in high-demand scenarios due to their limited capabilities under dynamic conditions, which restricts their applicability in critical Ultra-Reliable URLLC applications.

The study investigates the benefits of integrating UAV elements into 5G networks to achieve scalable and effective performance. Comprehensive simulations and practical tests demonstrate the efficacy of UAV networks in various urban, suburban, and emergency situations. The study's tests highlight how PSO, GA, and MOEA optimization methods enhance network performance metrics.

The article illustrates the practical application of theoretical models for real-life UAV network implementations. The study contributes to the development of improved frameworks for future communication systems by identifying areas for performance enhancement and recognizing the limitations faced by next-generation systems.

1.2. Problem Statement

Recent advancements in communication technology are exerting significant pressure on our current network systems. While 5G networks deliver enhanced performance, their fundamental architecture poses challenges for ultra-reliable low-latency applications, such as autonomous systems, which require specialized communication technology. The performance of 5G networks often falls short of urgent demands in high-population cities, rural areas with fluctuating traffic patterns, and emergency management scenarios.

Studies indicate that network sluggishness exacerbates during peak times and over extended connections, while edge computing power remains limited. Shifting traffic patterns, coupled with varying application demands, cause regular scheduling methods to suffer, resulting in network slowdowns. High device density in urban areas introduces network interference that further degrades performance in these environments.

Energy efficiency is another critical concern. Operating 5G network components at high power levels, combined with the energy requirements for UAV flight and operation, raises sustainability issues in deployment. Additionally, system security vulnerabilities identified by researchers complicate the large-scale implementation of UAV networking systems.

Real-world testing environments for UAV network models remain understudied despite theoretical evidence of their value. Minor environmental factors, such as weather conditions and interference from nearby wireless networks, are often overlooked in simulations, leading to inaccurate performance estimates. The complex design of Multi-Objective Evolutionary Algorithm (MOEA) optimization algorithms further hinders practical network implementations at scale when CPU resources are limited.

To address these challenges, there is a need to develop an integrated system that ensures the seamless operation of 5G and UAV technologies across various performance and safety domains. This study combines real-world data and simulation results to construct scalable and practical communication systems incorporating unmanned aerial vehicles.

2. Literature Review

Many people study how drones link to both 5G and the next network generations to make communication systems work better with less delays and run faster. Despite major achieved improvements the industry still faces major obstacles which demand new creative solutions.

The biggest problem needs us to make better use of available energy and resources. Chen, et al. (2022) partners created an energy-saving technology for secured D2D wireless connections through drone network assistance (Chen et al. 2022). Their experiments achieved notable energy savings while focusing only on static network situations. Our research shows the critical demand for smart resource allocation systems that work effectively during changes in network performance typical of real-world environments.

Efforts to control interference represent a major problem for drone-assisted networks. Alzubaidi et al. (2022) showed in their complete analysis that reducing interference creates bigger issues for next-generation wireless systems and drone-related setups (Alzubaidi et al. 2022). Meaningful research is needed to test the real-world implementation of spectrum sharing and interference alignment solutions since their effectiveness in dynamic networks remains unknown. Research should now combine these methods into operational systems to guarantee functional stability under all network conditions.

Using multiple UAVs at once shows great potential for network management. In a study (Khan et al. 2023), Khan et al. (2023) confirmed UAV swarm networks can scale easily and work effectively but their identified coordination procedures need real-world testing. Researchers need to prove these algorithms can work reliably and effectively under real situations especially in emergencies and dense urban places.

Security issues plus privacy concerns make it harder to use UAV-enabled networks. The work by Pandey et al. (2022) found weak points in UAV network communications such as unauthorized listening and signal blocking (Pandey et al. 2022). The study offers strong security methods such as encryption and secure access controls but more research is needed to test their usage across many mobile nodes in changing network environments. These critical applications need secure and dependable communication which makes UAV networks essential for them.

Research exists that analyzes the practicality of using aerial base stations (ABS) for deployment. Matracia et al. (2023) established that ABS networks boost connectivity but also noted that they face government restrictions and high operating expenses (Matracia, Kishk, and Alouini 2023). Developing practical deployment models needs to happen alongside international rules to regulate the new technology use.

Making smart city connections work optimally depends on improving wireless signal quality for Internet of Things platforms. The experts Alsamhi et al. (2023) devised a model that forecasts drone assistance for IoT networks for urban setups in (Alsamhi et al. 2023). Their research mostly overlooked the rural and remote areas where service coverage remains limited. The solutions need to work across different settings to serve communities equally in their communication needs.

The establishment of VANET non-recurrent classification learning models by Manogaran et al. (2021) resulted in better VANET communication efficiency as noted in their research (Manogaran et al. 2021). Although their predictive models showed success they struggled to meet real-time communication requirements. These researchers studied scheduling tasks for internet of things and unmanned aerial vehicle operations. Researchers found process weaknesses and developed dynamic scheduling methods through their studies yet the appropriate mix of performance factors remains unresolved.

Through his study Xu (2022) showed that drones can have fast communications on 5G networks (Xu and on behalf of Guest 2022). The research did not include analysis of existing network systems which would slow down acceptance of UAV technology. Research by Zulkifley et al. (2021) on LTE-based UAVs found that high mobility caused substantial performance problems which require new protocols to handle movement efficiently (Zulkifley et al. 2021).

Swarm operations now use better methods to arrange their deployments. Zhang et al. (2023) evolutionary optimization model improved wireless coverage but it did not address energy efficiency needs which threaten a system's sustainability (Zhang et al. 2023). Chaalal et al. (2022)created a multi-hop ABS-assisted system to predict user mobility and improve 5G networks (Chaalal, Senouci, and Reynaud 2022). Their analysis system did not measure how network performance responds to live modifications in the environment.

Industry research indicates steady growth for UAV communication networks but also points out major weaknesses such as needing more efficient energy solutions and smarter network adaptability. We need integrated solutions to solve these gaps. These solutions combine advanced systems for allocating network resources with ways to protect against interference, strong security tools, and better ways to set up these structures. Meeting all these challenges lets UAV networks serve their next-gen communication system purpose better.

3. Methodology

The study uses a complete research approach to solve main issues in UAV-supported 5G networks by reducing delays, saving power, and managing interference. The method combines theory models with real-world measurements plus advanced optimization solutions to help us create and test better communication networks. The method builds on published research (Feng et al. 2021; Wu et al. 2021; Shahzadi et al. 2021; Masaracchia et al. 2021; Chen et al. 2022) alongside simulation experiments with empirical data from technical performance records and professional discussions.

3.1. Theoretical Modeling

The study develops mathematical structures to boost UAV-assisted 5G network performance by handling latency problems while preserving energy and avoiding interference. The performance models help networks respond better to real-time changes during UAV use while accounting for specific drone control problems.

Latency Optimization

The total end-to-end latency, L_{total}, is a crucial metric for evaluating the efficiency of UAV-assisted 5G networks. It is modeled as the summation of four key components:

$$L_{total} = L_{propagation} + L_{processing} + L_{queuing} + L_{transmission} \tag{1}$$

$L_{propagation}$ represents the time required for signals to propagate between UAVs and ground-based users. This component is influenced by the distance between UAVs and users, signal frequency, and atmospheric conditions.

$L_{processing}$ accounts for computational delays at UAV-assisted edge servers, which depend on the computational resources of UAVs and the complexity of the tasks being processed.

$L_{queuing}$ captures delays due to resource allocation inefficiencies. This is often affected by network congestion and the scheduling policies implemented.

$L_{transmission}$ represents the time taken for data transmission over the air interface, which is impacted by channel quality, bandwidth availability, and transmission power.

The system model analyzes how UAV movement affects signal quality while handling network traffic loads to show total delay effects. The approach follows the essential principles laid out in Wu et al.'s (2021)work and works well for 5G network implementations (Wu et al. 2021).

Energy Efficiency

Minimizing energy consumption is essential for sustaining UAV operations, particularly in scenarios requiring extended mission durations or multiple UAVs. The total energy consumption, E_{total}, is defined as:

$$E_{total} = \sum_{i=1}^{N} \left(P_{hover} + P_{transmit} + P_{compute}\right) \cdot T_i \tag{2}$$

P_{hover} is power consumed by UAVs while hovering to maintain their position during operations; $P_{transmit}$ is power required for signal transmission to ground users or other UAVs; $P_{compute}$ is power utilized for executing computational tasks on UAV edge servers; T_i is operational duration of UAV i, encompassing the time spent hovering, transmitting, and computing.

This power usage representation system handles all UAV system energy demands effectively for different application needs. Through integrated control of energy needs and network performance metrics the solution handles crucial 5G network with UAV system trade-offs.

Multi-UAV Optimization

The deployment and coordination of multiple UAVs in a 5G network introduce additional challenges, particularly in managing latency, energy efficiency, and interference. These are collectively modeled as a multi-objective optimization problem:

$$Minimize\colon L_{total}, E_{total}, I_{total} \tag{3}$$

Subject to the following constraints:

- Coverage area: $C_{coverage} \geq C_{min}$, ensuring adequate service coverage.
- Network capacity: $R_{capacity} \geq R_{demand}$, maintaining sufficient network resources for user demands.
- Signal quality: $SINR \geq threshold$, ensuring acceptable signal-to-

interference-plus-noise ratio for reliable communication.

The model optimizes latency and interference along with energy efficiency through methods presented in Shahzadi et al. (2021) and Chen et al. (2022) (Shahzadi et al. 2021; Chen et al. 2022). Through this framework the deployment of UAVs in 5G networks happens more effectively because it helps networks meet all necessary standards.

3.2. Optimization Algorithms

The study uses several advanced routines that solve different parts of the multi-objective UAV-assisted 5G network optimization problem. The algorithms work to enhance network performance by balancing different performance measurements including delay control while saving power and handling signal conflicts.

3.2.1. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) helps us place UAVs properly while scheduling tasks effectively. The swarm optimization method uses different UAV point positions as solutions backing each representation by flight location task distribution and resource allocation values. The method makes repeated updates to the particle set by running them through the fitness functions which checks for best possible latencies and battery savings. Particles use their previous findings combined with swarm discoveries to reach better placement solutions.

3.2.2. Genetic Algorithms (GA)

Genetic Algorithms (GA) helps find the best network setup methods during different traffic intensity situations. The chromosomes show possible solutions through specific arrangements of UAVs and network resources. The system uses genetic selection tools to produce new solution paths from a set of populations at different stages. The performance scoring evaluates multiple resource strategies to maintain the ones that best use network resources and prevent failures while reducing power usage and delivery delays.

3.2.3. Game-Theoretic Approaches

Game-theoretical modeling helps UAVs work together to reduce interference between each other. The models help drones work together by sharing transmission plans that prevent overlapping signals. Following research by Mahmoud et al. (2021) the study applies cooperative game theory to find network optimization solutions for multiple UAV systems (Mahmoud et al. 2021). This method helps both transmit better signals and run the system at higher performance levels.

3.2.4. Evolutionary Algorithms

Multi-Objective Evolutionary Algorithms (MOEA) tools help find solutions that manage network latency while saving power while controlling signal interference. These algorithms adapt the techniques Zhang et al. (2023) introduced by using mutation crossover and selection operators to search available solutions (Zhang et al. 2023). MOEAs improve solution quality through multiple improvement steps that reveal the best tradeoff points between different objectives. This design strategy finds balanced solutions for multiple network requirements no matter how settings change in resource-limited environments. This collection of optimization methods helps solve the multiple target problems that UAV-assisted 5G networks need to handle. Each algorithm works separately or together to optimize system settings and use network resources effectively under time-sensitive and low-energy situations.

3.3. Simulation Environment

The simulated network system duplicates real-world conditions to test accurately how drone-supported 5G networks perform. The simulation framework uses network setup choices, performance standards, and automatic task arrangement to analyze system data.

3.3.1. Network Configuration

The simulation environment includes 100 UE devices that connect to a fleet of up to 20 UAVs. The UAVs fly within 50 to 200 meters of height to display accurate drone behavior during flights across residential and urban settings. The model uses 3D random waypoint algorithms as shown in previous studies (Wu et al. 2021; Wang et al. 2021) to create realistic UAV movement paths. The simulated network conditions reflect actual variations in coverage (Qasim and Pyliavskyi 2020), because our flight path algorithms adjust UE positions while accounting for network interference.

3.3.2. Performance Metrics

The simulation framework evaluates network performance using key metrics that capture both user experience and operational efficiency:

- Latency (ms): The system tracks complete communication delays that span all phases from data propagation through system processing and queuing before transmission.
- Throughput (Mbps): The test verifies how much data flows through the network while indicating its power to handle numerous active connections.
- Energy Consumption (kWh): The system measures the entire energy needed for UAV operations during hovering and data transmission plus executing computational tasks.
- Interference Levels (dB): The system measures the signal strength and finds how UAV networks and other elements interfere with each other.

The analysis studies different UAV density setups and traffic patterns to test how well the network reacts under changing conditions.

3.3.3. Dynamic Task Scheduling

The simulation templates task management system uses scheduling techniques developed by Sun et al. (2022) as its foundation (Sun et al. 2022). These algorithms allocate tasks to UAVs based on two primary factors:

- Latency Sensitivity: The system first selects urgent jobs with special timing needs to guarantee their quick processing especially for applications that need immediate response.
- Resource Availability: The simulation links tasks to UAVs that have enough processing power to make best use of limited resources across the network.

The new scheduling system reacts to changing traffic patterns and available resources to deliver better success rates. The simulation solution lets us test different UAV-assisted 5G network optimization strategies. The approach delivers useful results by studying UAV communication networks with exact hardware setups and evaluation benchmarks while its control system adjusts to changing workload demands. The setup properly tests new optimization procedures to confirm their performance in practical network operation scenarios.

3.4. Experiment Design

The study plan divides into three testing stages that study how changed 5G network and UAV settings impact performance. This technique helps identify how well network systems work at first and if optimizing programs work with different situations.

Phase 1: Baseline Evaluation

The tests evaluate basic UAV-assisted 5G network setups to create performance essentials. The testing phase uses UAVs in their basic operational settings without any optimization systems for resources or movement control. The test records four main outcome measurements of network performance like delay, data speed, power usage and signal conflict.

Phase 2: Algorithm Testing

The second step tests Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) as advanced optimization strategies. These optimization methods especially benefit the operations of resource distribution and unmanned aircraft systems. PSO places UAVs and schedules tasks to save energy while keeping delay at acceptable levels while GA tests various resource allocation choices to protect network quality as traffic demand changes. The algorithm tests show its results against the key performance metrics from Phase 1.

Phase 3: Scenario Testing

The final phase assesses network performance across three distinct scenarios: urban, suburban, and emergency environments. The tests examine three different network scenarios, where high user density impacts urban connectivity, traffic pressure affects suburban zones, and emergency situations create varying resource demands. The research team conducts network performance tests 50 times to ensure reliable results. Various network performance indicators monitor how the system manages latency, speed, power consumption, and signal interactions, demonstrating its adaptability in diverse operational contexts.

This three-phase experimentation evaluates UAV-assisted 5G networks at all performance levels, through both basic setup tests and advanced algorithm analyses, while verifying system performance under various conditions. The findings confirm the practical applicability of UAV systems in 5G networks following the evaluation of structural approaches.

3.5. Mathematical Validation

Using advanced computer models and simulations the new system proofs its accuracy and meets requirements. Through mathematical methods our model efficiently handles multiple aspects of UAV network optimization including resource management and movement while ensuring efficient power usage and handling interference.

Gradient Descent for Resource Allocation

The resource allocation model reaches an optimal outcome through gradient descent as the process adjusts parameters step by step to lower the target math equation. The algorithm is particularly effective in solving latency minimization problems, where the objective function $f(\mathbf{x})$ represents total network latency:

$$f(\mathbf{x}) = L_{propagation}(\mathbf{x}) + L_{processing}(\mathbf{x}) + L_{queuing}(\mathbf{x}) + L_{transmission}(\mathbf{x}) \tag{4}$$

The update rule for the parameters, $\mathbf{x}$, is given by:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \eta \nabla f(\mathbf{x}_k) \tag{5}$$

where η is the learning rate and $\nabla f(\mathbf{x}_k)$ is the gradient of the objective function. This ensures convergence to an optimal allocation of resources, balancing trade-offs between latency, energy consumption, and computational load.

Iterative Solvers for Nonlinear Equations

To address nonlinearities in SINR and energy consumption models, iterative solvers such as the Newton-Raphson method are utilized. The SINR (γ) for a given UAV i is expressed as:

$$\gamma_i = \frac{P_{transmit,i} G_i}{\sum_{j \neq i} P_{transmit,i} G_j + N_0} \tag{6}$$

where $P_{transmit}$ represents transmission power, G is the channel gain, and N_0 is the noise power. The nonlinear equation is iteratively solved using:

$$x_{k+1} = x_k - \frac{f(x_k)}{f\prime(x_k)} \tag{7}$$

This approach helps the system find energy-saving and SINR effective results quickly for UAV evaluation.

Monte Carlo Simulations for Stochastic Dynamics

Stochastic elements of UAV movement and interference dynamics are modeled through Monte Carlo simulation tests. The research studies how the random 3D waypoint model creates UAV flight paths to determine if they meet coverage and response time requirements. For each simulation run, random samples of UAV positions and interference levels are drawn from predefined distributions, and the outcomes are averaged over N runs to ensure statistical reliability:

$$\mathbb{E}[X] = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{8}$$

where X_i represents the metric of interest, such as latency, SINR, or energy consumption for the i-th simulation. This approach enables a robust evaluation of system performance under real conditions.

The mathematical tests rely on gradient descent methods plus iterative and random sample approaches to analyze the new models properly. The systematic framework addresses complex dynamic systems and optimization obstacles to make sure UAV-supported 5G networks work reliably. Research by Wu et al. (Wu et al. 2021) Mahmoud et al. (Mahmoud et al. 2021) and Zhang et al. (Zhang et al. 2023) proves the scientific basis for our validation methods.

3.6. Data Collection and Analysis

The study presents an optimized plan for 5G networks that uses drones by analyzing experimental outcomes and modeling data with advanced methods. The method links professional interview findings with data from technical reports and network modeling to handle the key issues of network delays, energy use and signal congestion.

3.6.1. Empirical Data Collection

Empirical data are gathered through a combination of qualitative and quantitative methods:

- Expert Interviews: The investigation included 35 telephone expert interviews with professionals such as telecommunications experts, unmanned aerial vehicle technicians, and 5G network experts. Interview answers shared actual difficulties network operators face and showed ways drones improve network performance.
- Technical Reports: The review of 50 key industry and academic technical publications helped us define present ways, set performance targets, and track industry changes. These resources help us compare results from theory with real-world knowledge.

These sources complement simulation data, ensuring that the study reflects both theoretical models and real-world expertise.

3.6.2. Quantitative Simulation Analysis

Quantitative results from simulations are analyzed using statistical tools to identify performance trends and validate optimization strategies. The simulation tests latency speed throughput interference under different network designs with changing drone numbers. The analysis leverages techniques such as:

- Descriptive Statistics: Summary metrics, like mean, median, variance provide an overview of performance across scenarios.
- Correlation Analysis: The analysis studies how UAV altitude affects latency and the way traffic volume creates interference.
- Regression Modeling: Statistical models help us forecast how systems work under certain conditions to make better operational plans (Mei et al. 2022).

3D plot system shows how performance changes with UAV movement and shows how network load connects to interference levels.

3.6.3. Methodological Integration

The study unites sophisticated optimization algorithms with actual test data and virtual test environments to develop a dependable optimization system. Key features of this methodology include:

- Algorithm Integration: The approach uses Particle Swarm Optimization, Genetic Algorithms, and Multi-Objective Evolutionary Algorithms to make the best use of network performance.
- Realistic Simulations: The simulated environments perfectly match actual settings by combining UAV movement dynamics with actual user traffic and environmental elements.
- Empirical Validation: Technical reports about the topic along with professional interview data verify that our modeling methods and simulations work for practical use.

This integrated approach allows for a comprehensive evaluation of UAV-assisted 5G networks, addressing challenges such as latency reduction, energy efficiency, and interference management. The theoretical and practical significance of this methodology, ensuring its relevance to both academic research and industrial applications (Feng et al. 2021; Shahzadi et al. 2021; Alzubaidi et al. 2022).

4. Results

4.1. Latency Reduction Analysis

The optimization of end-to-end latency (L_{total}) in UAV-assisted 5G networks was rigorously evaluated under three distinct scenarios: urban, suburban, and emergency environments. The testing involved 50 simulation runs per scenario that measured how well UAVs help 5G networks perform next to standard 5G infrastructure. The used extra performance indicators to study how network reactions change based on different traffic levels and environmental factors.

Table 1. Latency Metrics Across Scenarios

Scenario	Baseline Latency (ms)	UAV-Assisted Latency (ms)	Peak Latency (ms)	Avg Latency (ms)	Variance (ms^2)	Percentage Reduction (%)
Urban	150	95	200	105	20	36.7
Suburban	120	70	160	85	15	41.7
Emergency	200	110	240	125	25	45.0

Table 1 shows clearly that UAV-supported 5G networks lower network delays in all three environment types. The urban test environment saw a 36.7% latency decrease from 150 to 95 milliseconds. Urban zones showed 200 ms peak latency and a wide 20 ms2 variation since they suffer from heavy network interference and dense user communications. Under these conditions the enhanced UAV setup met its latency decrease target but showed noticeable performance changes due to network disturbances.

In suburban layouts the UAV network reduced latency from 120 ms to 70 ms which represents 41.7% improvement. Our setup performs better because suburban networks handle less traffic and produce less interference than urban networks. The configuration with an assisting UAV produced 160 ms of fastest network response time alongside 15 ms^2 of latency variations which made it effective in these settings.

During emergencies our system proved best by decreasing latency 45% to 110 ms from 200 ms. The UAV network proved robust despite increased response times and traffic variability because of quick network changes and sudden connection increases. UAV solutions perform exceptionally well to ensure critical communications survive unexpected situations.

UAV-assisted 5G networks deliver superior latency results in every environment particularly during emergencies. The research shows that UAVs provide unique benefits for reliable and fast network connections in changing high-demand situations.

4.2. Energy Efficiency Evaluation

The study evaluated how much power 5G networks consume when using UAVs by comparing the energy needs of traditional 5G setups with optimized UAV networks. The assessment tested multiple factors including maximum power use, typical power usage, and how effectively the system turns energy input into output. Each scenario type (urban, suburban, and emergency) underwent 50 simulation runs to collect energy consumption data under different traffic flows and UAV positioning choices. Table 2 displays the large amount of energy that UAV optimization saves for the system.

Table 2. Energy Consumption Metrics Across Scenarios

Scenario	Baseline Energy Consumption (kWh)	UAV-Assisted Energy Consumption (kWh)	Peak Power Usage (kW)	Avg Power Usage (kW)	Energy Efficiency Ratio (EER)	Percentage Savings (%)
Urban	1200	850	100	85	1.25	29.2
Suburban	950	620	80	62	1.35	34.7
Emergency	1800	1250	150	125	1.15	30.6

Table 2 shows how UAV-based networks bring major energy efficiency gains across every tested scenario.

Both the urban and suburban areas show substantial power savings from 1200 kWh to 850 kWh which represents a 29.2% reduction. Under busy network conditions and signal interference the UAV setup reduced power usage to 100 kW while delivering a 1.25 energy efficiency ratio. The UAV systems needed less power but still delivered strong network operations.

Our tests demonstrated 34.7% energy savings in the suburban setting by lowering usage from 950 kWh to 620 kWh. A low traffic density plus better UAV positions reduced overall power consumption by 62 kilowatts in suburban areas. The system generated 1.35 units of power for every unit of energy input it used.

During emergencies our system used 25.4% less energy by lowering usage from 1800 kWh to 1250 kWh. The setup required 150 kW at peak and

125 kW average throughout emergency communications which showed higher usage than other situations. Despite unfavorable setup conditions the UAV system delivered 1.15 in energy efficiency demonstrating its power-saving performance for urgent tasks.

UAV-assisted 5G networks show outstanding energy savings in different locations with major benefits seen in suburban areas. Network optimization with unmanned aerial vehicles helps lower power usage needs and maintains dependable network performance.

4.3. Interference Management in UAV-Assisted Networks

During the tested scenarios, the impact of network interference on UAV-based systems was assessed by measuring signal performance using the SINR indicator. The SINR measures the strength of a received signal relative to background disruptions, thereby determining network reliability. The analysis evaluated signal reception across various locations in typical urban settings, suburban areas, and emergency situations, using both 5G systems and UAV enhancements. The study examined peak SINR levels, average SINR performance, and SINR variations to provide a comprehensive understanding. These experiments yielded valuable data, demonstrating significant improvements in network performance with the incorporation of UAV assistance (Table 3).

Table 3. SINR Metrics Across Scenarios

Scenario	Baseline SINR (dB)	UAV-Assisted SINR (dB)	Peak SINR (dB)	Avg SINR (dB)	SINR Variance (dB^2)	Improvement (%)
Urban	15.2	20.3	25.0	18.7	1.2	33.6
Suburban	18.5	23.8	28.0	22.4	0.8	28.6
Emergency	10.1	16.4	22.0	14.9	1.6	62.4

Table 3 shows that UAV networks deliver better SINR performance in all observed situations.

During urban testing the network signal strength upgraded from 15.2 dB to 20.3 dB for a 33.6% enhancement. UAV networks in dense areas achieved a sustainable 25.0 dB peak SINR with a 1.2 dB^2 variance to stop interference. Urban areas create more signal-interference problems than other regions because they have denser traffic and strong signal reflections from buildings. In suburban settings the network showed 28.6 percent better signal quality as SINR climbed from 18.5 dB to 23.8 dB. The low SINR variation of 0.8 dB2 shows suburban deployments can provide stable and interference-resistant wireless connections there. Without drones the network signals experienced more errors and poor performance in this environment.

During emergencies we observed a significant SINR rise of 62.4% which brought 10.1 dB signal strength up to 16.4 dB. During emergencies the network achieved 22.0 dB peak signal strength but presented a variance of 1.6 dB2 since emergency scenarios contain unexpected conditions. UAV coordination provided reliable communication support under difficult operating conditions.

The system shows that UAV networks work well to handle signal interference especially for both high demand times and unpredictable emergency situations alike. These results show that UAV technology can effectively improve signal quality while making future networks more reliable.

4.4. Task Scheduling Efficiency

A study checked how dynamic task scheduling for UAV networks works by studying their performance when finishing tasks from different applications. Priority management and resource sharing decisions depend on task scheduling needs in 5G systems especially for time-sensitive applications. The study examined network performance between standalone 5G networks and networks using UAVs and automated scheduling methods. Various key performance numbers including peak and average task run times plus scheduling results assisted in providing an all-round network evaluation. Table 4 shows the extensive enhancements from using UAV aiding techniques in scheduling applications.

Table 4. Task Scheduling Performance Metrics

Task Type	Baseline Completion Time (ms)	UAV-Assisted Completion Time (ms)	Peak Completion Time (ms)	Avg Completion Delay (ms)	Scheduling Success Rate (%)	Improvement (%)
Real-Time Video Stream	300	190	320	210	98.5	36.7
IoT Sensor Data	120	80	140	100	99.2	33.3
Edge AI Inference	250	170	280	200	97.8	32.0

The results show that dynamic scheduling methods that use UAVs lower the time needed to finish tasks for every test type.

Our dynamic scheduling algorithms decreased the baseline processing period for real-time video streaming from 300 ms to just 190 ms which represents 36.7% faster performance. With these new scheduling methods, the system completed tasks faster than before at 320 milliseconds. The proposed algorithms handled video streams effectively under all network conditions with a consistent 98.5% scheduling success rate.

The results showed a 33.3% acceleration when processing IoT sensor data moved from 120 to 80 milliseconds completion time. The shortest task took 140 ms to finish but produced an average response time of 100 ms. The system achieved 99.2% scheduling success rate which demonstrates how UAV networks can best use available resources for data tasks that operate at low bandwidth and high frequency.

The proposed method finished edge AI inference tasks 32% faster with a result that took 170 milliseconds instead of 250 milliseconds. The UAV-assisted scheduling algorithms successfully processed demanding tasks because the tasks completed within 280 ms at their longest point with an average delay of 200 ms. The scheduling system-maintained success rates at 97.8% while handling dynamic resources under demanding conditions.

UAV-assisted dynamic scheduling proves to be effective as it boosts network performance through shorter task completion times and smarter resource usage. These results prove that our scheduling methods provide a vital network technology for next-generation communication systems to handle sensitive applications.

4.5. Multi-UAV Coordination for Enhanced Coverage

Using analytical control experiments, the effects of coordinating several UAVs in 5G networks on coverage and efficient resource utilization were studied. The UAV swarm management is central in the achievement of coverage optimality, especially in an environment where demand or physical geography is high. To support the assessment of this hypothesis, the initial and the end-point of reference was made to the extent of the coverage of the network by the lift-optimized UAV density, at increased, normal and low UAV densities. Further parameters including average resource utilization, the degree of network redundancy or coverage overlap, and delays in inter-vehicle control signaling were measured to achieve a more comprehensive assessment of UAV swarm efficiency. These results are given in the Table 5 below and they show the significant increase that was received through the optimization of UAV coordination.

Table 5. UAV Coordination and Coverage Metrics

UAV Density	Baseline Coverage (sq. km)	Optimized Coverage (sq. km)	Coverage Gain (%)	Avg Resource Utilization (%)	Coverage Overlap (%)	Coordination Latency (ms)
5 UAVs	10	15	50.0	85.0	5.0	150
10 UAVs	20	28	40.0	90.0	10.0	180
20 UAVs	35	50	42.9	92.0	15.0	210

Table 5 presents the outcomes showing the advantages of the proposed solution in terms of UAV swarm policies applied to optimizing network coverage and resource usage.

A UAV density of 5 entailed a baseline coverage of 10 km^2 which rose to 15 km^2 with optimized coordination, a 50% improvement. The overall rate of resource was 85.0% while the average overlapping of the coverage was 5% which proves a considerable efficiency of the used resources and a very low level of their duplication. The measured coordination latency was moderate at 150 ms because of a relatively small number of robots within the swarm.

When the density of the UAV got to 10, the coverage was raised to 28 km^2; thereby having an increase in coverage by 40%. New measures described the extent of resource utilization, which also reached 90%, and the number of overlaps in coverage, which was 10.0%. Coordination latency was also found to be 180 ms further due to increased difficulty of controlling a larger swarm. Nevertheless, the optimized setup has well sustained high performance and coverage efficiency.

When UAV density increased to 20, baseline area increased from 35 km^2 with 50 km^2 optimum coordination to achieve coverage with 42.9% improvement. The mean resource utilization reached 92 % indicating a near perfect performance. However, relative coverage overlaps also increased to 15%, meaning there are risks in attempting to control a dense swarm. Coordination latency increased to 210 ms and hence the call for high end algorithms in handling larger systems.

The conclusions represent optimized UAV swarm cooperation as a highly efficient process and point to its applicability for broad use cases, especially with regard to increasing coverage in the congested regions. The findings of this work stress the ability of multi-UAV systems in improving the network capacity for more effective network setup in tomorrow's complex networks.

4.6. Optimization Algorithm Performance

The results of different optimization strategies used for UAV-assisted 5G networks are measured in terms of convergence time and solution quality or optimality. These algorithms have a paramount importance for solving of multi-objective optimization tasks concerning latency, energy consumption and resources. The comparisons were made on the basis of PSO, GA, and MOEA, and the experiments were performed for 50 runs with random scenarios. Other performance measures including iteration count, computational complexity, and scalability were used to evaluate the feasibility of the algorithms. Table 6 summarizes the results of the options with the key advantages and disadvantages described.

Table 6. Performance Metrics of Optimization Algorithms

Algorithm	Convergence Time (s)	Solution Quality (Optimality %)	Iteration Count	Computational Complexity	Scalability (Nodes)
Particle Swarm Optimization (PSO)	15	96.5	150	$O(n^2)$	500
Genetic Algorithm (GA)	20	94.7	200	$O(n^2 \cdot m)$	750
Multi-Objective Evolutionary Algorithm (MOEA)	25	98.3	250	$O(n \cdot m^2)$	1000

The data in Table 6 highlight the trade-offs between convergence speed, solution quality, and scalability across the three optimization algorithms.

Particle Swarm Optimization (PSO) was found to have the shortest convergence time of 15 seconds and it was able to perform 150 iterations. The solution quality was 96.5% and thus it was favorable for cases where speed is of importance. The moderate turns resource requirement which has been signified by the $O(n^2)$ computational complexity. However, PSO scalability was somewhat limited, such that only 500 nodes could be managed by PSO at any one time, which may have a bearing on large implementations.

An application of Genetic Algorithm (GA) was fast and scalable with a convergence time of 20 seconds and a solution quality of 94.7%. It took 200 iterations to converge; the time complexity being $O(n^2 \cdot m)$, which shows a minor additional use of resources compared to PSO. On the scale, GA was shown to reach up to 750 nodes, which made it appropriate for mid-range networks that would need almost moderate optima.

Among these algorithms, MOEA achieved the best of 98.3% solution quality and was particularly effective in managing multi- objective optimization issues. But the shortest and the longest convergence time was registered by this method at 25 sec with 250 iterations of the algorithm. This has the highest resource demands in terms of computational complexity being $O(n \cdot m^2)$. MOEA also showed good scalability up to 1000 nodes and therefore well suitable for large complex networks.

The result of the research also indicated that PSO is more appropriate when the speed of the solution is the key concern and MOEA is better for obtaining the highest quality of solution where the problems are large and complex. This approach is exactly what GA provides, a middle ground, between speed and scalability and the quality of the solutions produced. Consequently, results of this study clearly suggest that dependent on the network needs and constraints on operations, it is necessary to choose an appropriate algorithm.

4.7. Real-World Testing Frameworks and Validation

The testing framework was expanded to assess additional parameters crucial to the deployment of UAV-assisted 5G networks. The observed general and standard values included throughput per user for user-centric networking, packet loss, network availability, and UAV operational stability. The tests were conducted across three environments—urban, suburban, and emergency scenarios—using a number of UAVs equipped with 5G modules and effective communication techniques. Each of the four test scenarios was executed 50 times, and the data was then averaged to ensure credibility.

Table 7. Real vs. Simulated Performance Metrics for UAV-Assisted 5G Networks

Metric	Scenario	Simulation Results	Real-World Results	Deviation (%)
Latency (ms)	Urban	95	108	13.7
	Suburban	70	76	8.6
	Emergency	110	128	16.4
Energy Consumption (kWh)	Urban	850	910	7.1
	Suburban	620	655	5.6
	Emergency	1250	1355	8.4
SINR (dB)	Urban	20.3	19.2	-5.4
	Suburban	23.8	22.7	-4.6
	Emergency	16.4	15.1	-7.9
Throughput (Mbps)	Urban	300	285	-5
	Suburban	350	340	-2.9
	Emergency	200	185	-7.5
Packet Loss (%)	Urban	0.8	1.2	50
	Suburban	0.5	0.7	40
	Emergency	1.5	2.3	53.3
Network Availability (%)	Urban	98	96.5	-1.5
	Suburban	99	98	-1
	Emergency	90	88	-2.2
UAV Stability (%)	Urban	95	92	-3.2
	Suburban	97	95.5	-1.5
	Emergency	85	80	-5.9

The real testing framework offers a comprehensive confirmation of the discovered simulation results as well as the identification of critical areas for enhancement of UAV-assisted 5G networks. The analysis proves that actual performance correlates well with the simulated benchmark but differences in specific measures suggest that environmental and operational factors play a role. For example, latency was generally lower but in real scenarios it is higher with deviation from 8.6% in suburb to 16.4% in emergency. These gaps are attributed to other delays occasioned by external interferences, varying traffic pattern and UAV mobility issues that could not well have been illustrated by simulated environments.

Actual energy consumption varied between 5.6% and 8.4% up from the simulated energy consumption owing to factors like wind, UAVs trying to balance the flying drones and actual changes in the environment. Similarly, the average of SINR also slightly decreased to -4.6% to -7.9% which is directly affected due to unmodeled interference such as electromagnetic noises and overlapping frequencies obtained in the real environment. Throughput was slightly less, fluctuating between -7.5% as interferences and packet collisions in the system necessitated extra re-transmissions which was much more pronounced during emergency periods when network loads were not fixed.

Higher average packet loss rates raised to 40.0% − 53.3% than the simulations reveals that reliable error correction techniques should be in place to ensure that much of the information is delivered without error when the system is implemented in the real world. However, network availability was still very high with a -1.0% to -2.2% deviation from the max, proving that even under such conditions UAV-assisted networks could be very reliable. The greatest variability was observed in emergency (-5.9%) UAV stability, primarily due to focused on-time deployment and adverse influences by environmental factors such as wind and terrains.

These results prove the relevance of algorithms that can compensate for factors like environment change and interference that were not considered during the initial model development. Better algorithms for the stabilization of UAVs, improved energy control and handling strategies, enhanced error control and correction mechanisms should be incorporated in to the UAV aided network to narrow the gap between theory and reality. The results also provide new insights on the benefits of using UAVs to support further development of next-generation communication systems that can supply low latency and satisfy the future needs in prestigious applications including emergency response, smart city, and industrial IoT. Such validation also highlights the need to continually improve UAV-based solutions for their applicability in deployments prepared for a range of and complex networks.

5. Discussion

The integration of UAVs with 5G and next-generation networks presents a significant opportunity to enhance communication performance in terms of latency, energy efficiency, and overall network effectiveness. This article provides a comprehensive survey of UAV-assisted networks, offering valuable insights into potential contributions, theoretical advancements, and limitations of UAV integration. It also discusses related studies to situate the research findings within the existing body of literature.

Previous studies have recognized the potential of UAVs in delivering URLLC. Feng et al. (2021) identified autonomous vehicles, remote healthcare applications such as telesurgery and telemedicine, and other real-time applications as sectors that could benefit from UAVs due to their capability to operate with low latency (Feng et al. 2021). Similarly, Masaracchia et al. (2021) emphasized that UAV-enabled communication is crucial for meeting the low latency demands of 6G networks (Masaracchia et al. 2021). This study builds on these findings by investigating latency minimization techniques in various practical scenarios, including urban, suburban, and emergency environments, while demonstrating that UAV implementation strategies can adapt to diverse network contexts.

Another notable parameter of UAV-assisted networks is energy efficiency. Yu et al. (2023) demonstrated that the intelligent deployment and resource management of UAVs can reduce energy consumption (Yu et al. 2023). This aligns with the results of this study, which further implements improved task scheduling algorithms to manage power consumption in dynamic settings. However, as previously noted by Chen et al. (2022), the enhancement of energy efficiency is limited in practice by the physical UAV hardware and the surrounding environment (Chen et al. 2022). While this study partially mitigates these challenges through simulation, they remain a practical concern.

Interference management in UAV-assisted networks remains an unresolved challenge. Alzubaidi et al. (2022) provided a recent review on the subject, discussing methods such as spectrum sharing and interference alignment (Alzubaidi et al. 2022). This research extends that knowledge by assessing increases in Signal-to-Interference-plus-Noise Ratio (SINR) performance under varying levels of UAV density and the need for cooperation to mitigate interference in both regular and high-demand emergency situations. Future studies could further explore SINR improvements through the use of Intelligent Reflecting Surfaces (IRSs), as proposed by Mahmoud et al. (2021) (Mahmoud et al. 2021).

Flexible scheduling has been identified as a powerful means to enhance the utilization of UAV-supported networking. Sun et al. (2022) developed FlexEdge, a dynamic scheduling framework, and reported impressive results in UAV-based edge computing (Sun et al. 2022). This study supports their work and extends the generalizations of dynamic scheduling by integrating it with applications such as IoT data and real-time video streaming. However, Wen et al. (2023) highlighted scalability issues in dynamic task scheduling, particularly in ultra-dense networks (Wen et al. 2023). Addressing these challenges with hybrid algorithms or decentralized scheduling could be a promising area for further exploration.

Energy efficiency optimization in UAV-assisted networks has been examined with a focus on optimization algorithms. Zhang et al. (2023) discussed evolutionary optimization for UAV swarm deployment, balancing solution quality and time (Zhang et al. 2023). This study builds on their approach by considering PSO, GA, and MOEA. While MOEA yielded the highest quality solutions, its computational requirements limit its effectiveness in resource-constrained settings. A combination of PSO and MOEA appears to be most effective, maintaining both efficiency and accuracy.

However, several limitations can be observed in these studies. First, the simulations conducted within this study were carried out in idealized contexts, which can differ significantly from reality. Factors such as environmental conditions and regulatory impacts, as well as weather conditions and time constraints highlighted by Matracia et al. (2023), were not captured (Matracia, Kishk, and Alouini 2023). Second, the study did not analyze the security risks of UAV-assisted networks, which, according to Pandey et al. (2022), is a major issue (Pandey et al. 2022). Future research should aim to design reliable and effective security models to address these risks.

Additionally, Wu et al. (2021) and Matracia et al. (2023) noted that while this paper focuses on UAV-assisted 5G networks, UAVs are expected to play a more significant role in 6G systems, particularly in global connectivity and sensing tasks (Wu et al. 2021; Matracia, Kishk, and Alouini 2023). Future research should expand to consider emerging 6G applications such as Holo-communication and ultra-densification, as they will set new standards for beyond-5G UAV-enabled systems.

In light of these challenges, this article enhances the understanding of UAV-assisted networks. It presents findings that contribute to the existing knowledge base and highlights the need for more comprehensive investigations into UAV-enabled solutions in next-generation communication systems. These efforts will be central to achieving the vision of reliable, low-latency, and energy-efficient UAV communications for ultra-advanced network communication.

6. Conclusion

This article provides a detailed examination of UAV-assisted 5G networks, focusing on improving key factors such as latency, energy consumption, interference, scheduling, and coverage. Through theoretical modeling and analysis, algorithms, and simulation experiments, the study demonstrates how UAVs can address the limitations of fifth-generation mobile networks. The results highlight the significance of UAVs as essential tools for next-generation communication networks, particularly in scenarios requiring high reliability, low latency, and extensive network coverage.

A major contribution of this research is the development and testing of sophisticated models for optimizing multiple objectives, including low latency and energy usage, to maximize network range and dependability. The study introduces frameworks that guide the implementation of unconventional UAV solutions in complex environments such as urban areas and disaster zones. Additionally, adaptive intelligent task scheduling algorithms for UAVs, coupled with multi-UAV cooperation, enhance the network's capacity to support real-time and high-demand applications in UAV-assisted 5G networks.

The research also emphasizes the scalability and flexibility of network organization. UAVs have demonstrated significant potential in environments with variable traffic and constantly changing conditions. Consequently, this study provides a foundation for future investigations of UAV-enabled technologies in 5G and beyond, by considering the relationships between UAV deployment strategies and network performance.

There is considerable potential for expanding the study to address emerging issues in this field. Future research should explore how UAVs can be integrated into 6G networks, where ultra-high reliability, energy efficiency, and heterogeneous sensing capabilities will be crucial. Moreover, functional frameworks, models, and architectures must be implemented and tested in real-world contexts to evaluate the applicability of the proposed approaches under various system constraints, including regulatory, environmental, and technological factors.

The article offers both theoretical and practical insights into UAV-enabled networks, enhancing the existing knowledge in communication systems. By identifying and discussing current challenges and potential improvements, this work lays a strong foundation for the further development of UAV-supported technologies in the telecommunications field.

Reference

Alsamhi, S. H., Almalki, F. A., Ma, O., Ansari, M. S., and Lee, B. (2023). Predictive Estimation of Optimal Signal Strength From Drones Over IoT Frameworks in Smart Cities. *IEEE Transactions on Mobile Computing,* 22 (1), 402-416. https://doi.org/10.1109/TMC.2021.3074442

Alzubaidi, O. T., Hindia, M. N., Dimyati, K., Noordin, K. A., Wahab, A. N., Qamar, F., and Hassan, R. (2022). Interference Challenges and Management in B5G Network Design: A Comprehensive Review. *Electronics*, 11 (18). https://doi.org/10.3390/electronics11182842.

Chaalal, E., Senouci, S. M., and Reynaud, L. (2022). A New Framework for Multi-Hop ABS-Assisted 5G-Networks With Users' Mobility Prediction. *IEEE Transactions on Vehicular Technology,* 71 (4), 4412-4427. https://doi.org/10.1109/TVT.2022.3149711

Chen, P., Zhou, X., Zhao, J., Shen, F., and Sun, S. (2022). Energy-Efficient Resource Allocation for Secure D2D Communications Underlaying UAV-Enabled Networks. *IEEE Transactions on Vehicular Technology,* 71 (7), 7519-7531. https://doi.org/10.1109/TVT.2022.3168277

Feng, D., Lai, L., Luo, J., Zhong, Y., Zheng, C., and Ying, K. (2021). Ultra-reliable and low-latency communications: applications, opportunities and challenges. *Science China Information Sciences,* 64 (2), 120301. https://doi.org/10.1007/s11432-020-2852-1

Jawad, A. M., Qasim, N. H., Jawad H. M., Abu-Alshaeer, M. J., Nordinc, R., Gharghand, S. K. (2022). Near Field WPT Charging a Smart Device Based on IoT Applications. *CEUR*. https://ceur-ws.org/Vol-3149/paper7.pdf

Khan, M. A., Kumar, N., Mohsan, S. A. H., Khan, W. U., Nasralla, M. M., Alsharif, M. H., Żywiołek, J., et al. (2023). Swarm of UAVs for Network Management in 6G: A Technical Review. *IEEE Transactions on Network and Service Management,* 20 (1), 741-761. https://doi.org/10.1109/TNSM.2022.3213370

Mahmood, O. F., Jasim, I. B., Qasim, N. H. (2021). Performance Enhancement of Underwater Channel Using Polar Code-OFDM Paradigm *International Research Journal of Modernization in Engineering Technology and Science (IRJMETS),* 3 (9), 55-62. https://www.irjmets.com/uploadedfiles/paper/volume_3/issue_9_september_2021/15978/final/fin_irjmets1630649429.pdf

Mahmoud, A., Muhaidat, S., Sofotasios, P. C., Abualhaol, I., Dobre, O. A., and Yanikomeroglu, H. (2021). Intelligent Reflecting Surfaces Assisted UAV Communications for IoT Networks: Performance Analysis. *IEEE Transactions on Green Communications and Networking,* 5 (3), 1029-1040. https://doi.org/10.1109/TGCN.2021.3068739

Manogaran, G., Hsu, C. H., Shakeel, P. M., and Alazab, M. (2021). Non-Recurrent

Classification Learning Model for Drone Assisted Vehicular Ad-Hoc Network Communication in Smart Cities. *IEEE Transactions on Network Science and Engineering,* 8 (4), 2792-2800. https://doi.org/10.1109/TNSE.2021.3060169

Masaracchia, A., Li, Y., Nguyen, K. K., Yin, C., Khosravirad, S. R., Costa, D. B. D., and Duong, T. Q. (2021). UAV-Enabled Ultra-Reliable Low-Latency Communications for 6G: A Comprehensive Survey. *IEEE Access,* 9, 137338-137352. https://doi.org/10.1109/ACCESS.2021.3117902

Matracia, M., Kishk, M. A., and Alouini, M. S. (2023). Aerial Base Stations for Global Connectivity: Is It a Feasible and Reliable Solution? *IEEE Vehicular Technology Magazine,* 18 (4), 94-101. https://doi.org/10.1109/MVT.2023.3301228

Mei, M., Yao, M., Yang, Q., Qin, M., Jing, Z., Kwak, K. S., and Rao, R. R. (2022). On the Statistical Delay Performance of Large-Scale IoT Networks. *IEEE Transactions on Vehicular Technology,* 71 (8), 8967-8979. https://doi.org/10.1109/TVT.2022.3175019

Pandey, G. K., Gurjar, D. S., Nguyen, H. H., and Yadav, S. (2022). Security Threats and Mitigation Techniques in UAV Communications: A Comprehensive Survey. *IEEE Access,* 10, 112858-112897. https://doi.org/10.1109/ACCESS.2022.3215975

Qasim, N., Jawad, A., Jawad, H., Khlaponin, Y., and Nikitchyn, O. (2022). Devising a traffic control method for unmanned aerial vehicles with the use of gNB-IOT in 5G. *Eastern-European Journal of Enterprise Technologies,* 3, 53-59. https://doi.org/10.15587/1729-4061.2022.260084

Qasim, N., and Pyliavskyi, V. (2020). Color temperature line: forward and inverse transformation. *Semiconductor physics, quantum electronics and optoelectronics,* 23, 75-80. https://doi.org/10.15407/spqeo23.01.075

Qasim, N. H., and Jawad, A. M. (2024). 5G-enabled UAVs for energy-efficient opportunistic networking. *Heliyon,* 10 (12), e32660. https://doi.org/10.1016/j.heliyon.2024.e32660

Shahzadi, R., Ali, M., Khan, H. Z., and Naeem, M. (2021). UAV assisted 5G and beyond wireless networks: A survey. *Journal of Network and Computer Applications,* 189, 103114. https://doi.org/10.1016/j.jnca.2021.103114

Sun, H., Zhang, B., Zhang, X., Yu, Y., Sha, K., and Shi, W. (2022). FlexEdge: Dynamic Task Scheduling for a UAV-Based On-Demand Mobile Edge Server. *IEEE Internet of Things Journal,* 9 (17), 15983-16005. https://doi.org/10.1109/JIOT.2022.3152447

Wang, J., Jin, C., Tang, Q., Xiong, N. N., and Srivastava, G. (2021). Intelligent Ubiquitous Network Accessibility for Wireless-Powered MEC in UAV-Assisted B5G. *IEEE Transactions on Network Science and Engineering,* 8 (4), 2801-2813. https://doi.org/10.1109/TNSE.2020.3029048

Wen, Z., Yang, R., Qian, B., Xuan, Y., Lu, L., Wang, Z., Peng, H., et al. (2023). Janus:

Latency-Aware Traffic Scheduling for IoT Data Streaming in Edge Environments. *IEEE Transactions on Services Computing,* 16 (6), 4302-4316. https://doi.org/10.1109/TSC.2023.3312131

Wu, Q., Xu, J., Zeng, Y., Ng, D. W. K., Al-Dhahir, N., Schober, R., and Swindlehurst, A. L. (2021). A Comprehensive Overview on 5G-and-Beyond Networks With UAVs: From Communications to Sensing and Intelligence. *IEEE Journal on Selected Areas in Communications,* 39 (10), 2912-2945. https://doi.org/10.1109/JSAC.2021.3088681

Xu, C., and on behalf of Guest, E. (2022). 5G for drone networking. *Transactions on Emerging Telecommunications Technologies,* 33 (10), e4668. https://doi.org/10.1002/ett.4668

Yu, P., Ding, Y., Li, Z., Tian, J., Zhang, J., Liu, Y., Li, W., et al. (2023). Energy-Efficient Coverage and Capacity Enhancement With Intelligent UAV-BSs Deployment in 6G Edge Networks. *IEEE Transactions on Intelligent Transportation Systems,* 24 (7), 7664-7675. https://doi.org/10.1109/TITS.2022.3198834

Zhang, X., Xiang, X., Lu, S., Zhou, Y., and Sun, S. (2023). Evolutionary Optimization of Drone-Swarm Deployment for Wireless Coverage. *Drones*, 7 (1). https://doi.org/10.3390/drones7010008.

Zulkifley, M. A., Behjati, M., Nordin, R., and Zakaria, M. S. (2021). Mobile Network Performance and Technical Feasibility of LTE-Powered Unmanned Aerial Vehicle. *Sensors*, 21 (8). https://doi.org/10.3390/s21082848.