Optimized UAV-Based Connectivity Solutions for Urban IoT Networks

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***Abstract*—The rapid growth of the Internet of Things (IoT) in cities has resulted in a dense deployment of devices such as sensors and smart meters. These devices necessitate a steady and reliable internet connection. Traditional cellular networks, such as NB-IoT and LTE Cat-M, need help to meet these demands where the performance of current infrastructure has severely degraded due to high device density. As an alternative to existing cell towers, Unmanned Aerial Vehicle Base Stations (UAV-BSs) are proposed in this paper to address this challenge. These UAV-BSs act as mobile cell towers and are strategically placed in regions with a high concentration of IoT devices to improve network coverage and capacity. Furthermore, Tethered UAVs (TUAVs) powered by robotic Cellular-on-Wheels (COW) units support a robust backhaul link between the UAV-BSs and the network core. The study used the K-means algorithm, a machine-learning technique that clusters IoT devices according to their spatial distribution, to select the optimal places for the UAV-BSs. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are then used to refine the positions, systematically investigating multiple UAV-BSs placements to discover the most effective arrangement. Finally, the paper utilizes a new data transmission technique, the 'Mini slots' scheduling algorithm, to improve data exchange efficiency between IoT devices and UAV-BSs.**

***Keywords*—Internet of Things, Unmanned Aerial Vehicle Base Stations, Cell-on-Wheels, Tethered Unmanned Aerial Vehicles, Machine Learning Algorithms, Mini-slot Scheduling, Network Optimization.**

I. Introduction

The widespread adoption of Unmanned Aerial Vehicle (UAV) technology has significantly influenced many sectors, including commercial, military, and civilian areas. It has also become crucial in shaping urban environments, especially against the backdrop of the Internet of Things (IoT) revolution. Urban residents, from everyday commuters utilizing wearables for immediate data access to professionals leveraging smart applications for enhancing their tasks, are witnessing the transformative impact of the Internet of Things (IoT) [1]. Both private and commercial sectors benefit immensely from this interconnected ecosystem.

Traditional urban infrastructure often struggles, particularly during cellular network disruptions or in high-density settings. The goal is to restore the connectivity and ensure it has been optimized and can adapt to the diverse requirements of IoT applications. In this context, UAVs, especially the Unmanned Aerial Vehicle Base Stations (UAV-BSs) [2], [3], solve the connectivity dilemma. With their ability for flexible deployment, low latency, and efficient resource allocation, UAV-BSs have the potential to significantly improve the Quality of Service (QoS) in urban environments [4]. Leveraging their role is essential, especially when conventional infrastructure might need to be improved.

In our study, we combine the benefits of the K-means clustering algorithm [5] [6] with the Particle Swarm Optimization (PSO) [7] and Genetic Algorithm (GA) techniques. This combined approach, designed specifically for urban scenarios, aims to address the varied demands of the IoT framework.

Additionally, data management remains a significant consideration in IoT systems. Our proposed mini-slot scheduling mechanism, crafted for urban IoT settings, emphasizes efficient data transfer, prompt scheduling, and real-time processing. To enhance our approach, we integrate Cell-on-Wheels (CoW) units [8] and Tethered UAVs (TUAVs) [9] into the system. These UAVs are essential for improving connectivity in densely populated areas. Given urban IoT's myriad challenges, our strategy focuses on the optimal placement of UAV-BSs and robust backhaul connectivity. This approach maximises data transfer speeds while ensuring the lowest possible latency.

The paper is structured in the following manner: Section II describes our system model. Section III lays out the problem definition. Section IV details our solution approach. Section V presents simulation results and their discussion. Section VI concludes the paper, summarizing key points and potential future work.

II. System Model

The proposed system model presented in Fig. 1 represents an urban IoT network constituted by a set of IoT devices, denoted by $I = i_1, i_2, ..., i_M$, and a cluster of UAV-BSs, symbolized as $T = t_1, t_2, ..., t_N$. Every IoT device and UAV-BS is equipped with a single antenna, and the IoT devices engage in data-forwarding communication with the UAV-BS in their proximity.

A. Communication Phase

During the front-haul phase, an IoT device denoted as i communicates with a UAV-BS designated as j.

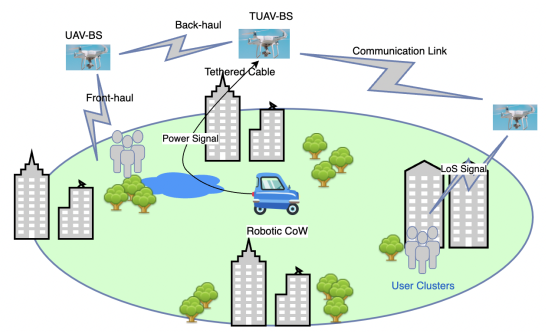

Fig. 1. System Model.

In the subsequent back-haul phase, the UAV-BS j establishes communication with a TUAV-BS denoted as k. The Euclidean distance between any device i and its corresponding base station j (either a UAV-BS or TUAV-BS, depending on the phase) is represented by $d_{i,j}$. This distance is calculated based on their Cartesian coordinates:

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + z_j^2}. \quad (1)$$

We adopt a free-space path loss model for communication in a sub-6 GHz band. For this study, we measure distance ($d_{i,j}$) in meters (m) and frequency (f_j) in gigahertz (GHz). The resulting path loss $\delta_{i,j}$, given in decibels (dB), is calculated as follows [10]:

$$\delta_{i,j} = 20\log_{10}(d_{i,j}) + 20\log_{10}(f_j) - 147.55. \quad (2)$$

In this equation, ($d_{i,j}$) is the distance between the i^{th} and j^{th} nodes in meters, and (f_j) is the frequency in GHz.

We take into account small-scale fading effects when calculating channel gains. The channel gain ($h_{i,j}$) between device i and base station j is calculated using the formula:

$$h_{i,j} = \beta_{i,j} 10^{-\delta_{i,j}/10}. \quad (3)$$

Here, $\beta_{i,j}$ is the path loss at a reference distance, and $\delta_{i,j}$ is the path loss between the device i and base station j, as calculated in the earlier equation.

Next, we calculate the Signal-to-Noise Ratio (SNR) for the communication link between the device i and the base station j. We represent this ratio as $\gamma_{i,j}$ and calculate it using the following equation:

$$\gamma_{i,j} = \frac{p_{i,j} h_{i,j}}{\sigma^2}. \quad (4)$$

In this equation, $p_{i,j}$ is the transmit power from the device i to the base station j, $h_{i,j}$ is the channel gain between the device i and the base station j, and σ^2 is the noise power.

B. Throughput

In this study, the total achievable throughput for the network, symbolized as R_{total}, is calculated by evaluating all possible device-to-base station pairings. The equation for this calculation is as follows:

$$R_{\text{total}} = \sum_{i \in I, j \in J} B_{i,j} \log_2(1 + \gamma_{i,j}). \quad (5)$$

In this equation, $B_{i,j}$ refers to the bandwidth assigned for the communication link between device i and base station j, representing the maximum volume of data that can be transferred over this link within a given time frame. The variable J takes on different representations depending on the communication phase: during the front-haul phase, J represents T, the set of UAV-BSs that receive data from the user IoT devices. In contrast, during the back-haul phase, J symbolizes $G = g_1, g_2, ..., g_O$, representing the data transmission from the UAV-BSs to a TUAV equipped robotic vehicle, often referred to as a COW.

This research aims to optimize the positioning of the UAV-BSs to maximize the total network throughput, denoted as R_{total} while considering practical limitations such as mobility and communication range. By adopting this strategic approach, the intention is to develop a robust and efficient system model for managing complex urban IoT networks.

III. Problem Formulation

In the urban IoT network under consideration, each IoT device $i \in I$ generates data transmitted to its associated UAV-BS $t \in T$. The operating time is divided into n time slots to manage this process. These slots are subdivided into mini-slots based on the strategy employed, such as the Normal Slots or Mini Slots scheme [11].

Normal Slots: Traditionally, the operation time is divided into fixed-length slots in many communication systems. These slots facilitate the orderly transmission of data from devices to base stations. Each slot could accommodate a packet of data or multiple packets, depending on the system's design.

Mini Slots: In dynamically varying environments like urban IoT networks, where the data generation rate might not be consistent (e.g., some IoT devices might generate data sporadically or in smaller quantities), utilizing a full slot might be inefficient. Here, "Mini Slots" come into the picture. By subdividing a normal slot into smaller intervals or "mini-slots", the system can more efficiently cater to devices with varied data requirements. This ensures that devices with smaller data packets don't have to wait for an entire slot, thus improving resource utilization and reducing latency.

Our primary goal is to establish an equilibrium between the aggregate data rate R_{total} and the total communication delay D_{total}, taking into account both schemes. The total communication delay is represented as:

$$D_{\text{total}} = \sum_{i \in I} D_{i,\text{comm}}, \quad (6)$$

where $D_{i,\text{comm}}$ indicates the communication delay for IoT device i. This is a function $f(d_{i,t}, s_{i,t})$ of the distance $d_{i,t}$ between IoT device i and its associated UAV-BS t, and the assigned slot or mini-slot $s_{i,t}$ for IoT device i at UAV-BS t. Similarly, the aggregate data rate is denoted as:

$$R_{\text{total}} = \sum_{i \in I} R_i. \tag{7}$$

Here, R_i symbolizes the data rate for IoT device i. As a result, we can formulate:

$$D_{i,\text{comm}} = f(d_{i,t}, s_{i,t}), \quad \forall i \in I, t \in T, \tag{8}$$

$$R_i = g(d_{i,t}, s_{i,t}), \quad \forall i \in I, t \in T. \tag{9}$$

In setting up UAV-BSs, it's crucial to consider certain limits for optimal performance. 1) A significant limit is the coverage distance from each UAV-BS, denoted as t, to all connected devices, represented as i in set I. This constraint is mathematically expressed as:

$$\sum_{i \in I} d_{i,t} \leq D_t, \quad \forall t \in T, \tag{10}$$

where D_t is the maximum distance the t-th UAV-BS can cover. This constraint ensures the total distance from a UAV-BS to all its connected devices does not exceed D_t. Adhering to this limit is vital as a UAV-BS operating beyond its capacity (D_t) might face service and operational issues. Ensuring each UAV-BS only connects to devices within its coverage limit (D_t) prevents overload and maintains service quality and effective operation. 2) A slot scheduling constraint must be applied to each IoT device i as a slot $s_{i,t}$ at its associated t-th UAV-BS:

$$\sum_{i \in I} s_{i,t} = n, \quad \forall t \in T. \tag{11}$$

The equation asserts that for each UAV-BS t, the total number of slots assigned to all IoT devices must equal n, the predefined total number of available slots. This rule applies to every UAV-BS. To address this problem, the following steps are adopted:

- Using K-means, PSO, or GA to group IoT devices by their respective locations and assigning each group to a UAV-BS; When deciding between K-means, PSO, or GA for grouping IoT devices by location and assigning each to a UAV-BS, consider the problem's complexity, computation time, and desired solution quality. K-means is suitable for simpler structures and quicker computation. At the same time, PSO and GA excel in handling complex, non-linear problems, potentially offering higher-quality solutions at the expense of increased computational time and implementation effort.
- Scheduling IoT devices in each group into slots or mini-slots using a Round Robin algorithm, depending on whether normal or mini-slots are used.

By arranging clustering and scheduling in this manner, we can achieve an optimal balance between aggregate data rate R_{total} and total communication delay D_{total}.

IV. Solution Approach and Algorithm Descriptions

Our method addresses communication challenges in urban IoT by focusing on: (1) cluster formation, (2) UAV-BS positioning, and (3) mini-slot scheduling. The main objective is to reduce the communication delay in the IoT network. This reduction in delay is anticipated to concurrently enhance the overall throughput and coverage of the network, contributing to more efficient and reliable communication among the IoT devices and the UAV-BS.

A. Cluster Formation

We use methods like K-means, PSO, and GA to group IoT devices together. The main goal is to place UAV-BSs in spots that help make communication as fast as possible. We test each method to see which one makes communication the quickest. The one that gives the best results, helping us achieve the fastest communication, is then chosen for further use in the network.

1) K-means Clustering: In the K-means approach, each IoT device is associated with the nearest UAV-BS. The UAV-BS position is adjusted based on the centroid of the assigned IoT devices. This process is repeated until the UAV-BS positions converge or a maximum number of iterations is reached. The objective is expressed as:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{M} ||x_{ij} - \mu_i||^2, \tag{12}$$

where μ_i is the position of the i-th UAV-BS and x_{ij} is the j-th IoT device assigned to the i-th UAV-BS.

B. UAV-BS and TUAV Positioning

This section describes the algorithms used to determine the optimal positions of both the UAV-BS and the TUAV. We employ the same algorithm for positioning both entities, prioritizing the reduction of communication delay as the main objective. After determining the positions for UAV-BS, we establish the locations for Robotic CoWs, which tether the UAVs. Factors like distance to the charging station and UAV battery life are considered.

1) PSO for UAV-BS and TUAV Positioning: PSO is utilized to identify the best positions for both UAV-BS and TUAV in the urban space.

a) Design Parameter: Each particle in the PSO represents a possible position for UAV-BS and TUAV.

b) Objective Function: The primary aim is to minimize the communication delay. The delay metric evaluates the fitness of each particle. Particles refine their positions considering individual and global best positions.

2) GA for UAV-BS and TUAV Positioning: Similarly, GA is used for optimizing the positions of UAV-BS and TUAV.

a) Design Parameter: In GA, each chromosome symbolizes a potential position for UAV-BS and TUAV.

b) Objective Function: The objective continues to be the reduction of communication delay. This delay evaluates chromosomes. GA processes involve:

1) Selection: Choose chromosomes based on fitness.
2) Crossover: Pair and combine chromosomes to create offspring.
3) Mutation: Introduce random mutations to ensure genetic diversity.

C. Mini-slot Scheduling

To efficiently manage communication, a mini-slot scheduling approach is employed. The operation time T is divided into N mini-slots. Each IoT device is given a specific mini-slot for communication using a Round-Robin method.

V. Simulation Results and Discussions

Our simulation environment was designed using Python, taking advantage of its comprehensive suite of scientific libraries. We primarily used `numpy` for array manipulations, `matplotlib` for graphical data representation, `sklearn` for initial user clustering, `pyswarms` for executing PSO, and `DEAP` for GA computations [12]. The parameters set for the simulation are displayed in Table I.

TABLE I
Simulation Parameters

Parameter	Value	Description
Area	5km $\times$ 5km	Square area for simulation
f_{t} (Hz)	3.5×10^9	The carrier frequency (3.5 GHz for 5G sub-6GHz)
β	1	Small scale fading coefficient
p_{t} (dBm)	20	Transmit power
σ^2 (dBm)	-94	Noise power
σ_{shadow} (dB)	8	Shadowing standard deviation
n_{users}	500	Number of IoT devices
n_{clusters}	5	Number of clusters
$c1$, $c2$, w	0.5, 0.3, 0.9	PSO parameters
$n_{\mathrm{particles}}$	10	Number of particles in PSO
$n_{\mathrm{generations}}$ (PSO)	100	Number of generations in PSO
n_{pop}	50	Population size in GA
cxpb	0.5	Crossover probability in GA
mutpb	0.2	Mutation probability in GA
$n_{\mathrm{generations}}$ (GA)	40	Number of generations in GA
N	5	Number of UAVs
h (m)	80	Altitude of the UAVs
T (s)	360	Total observation time
ΔT (s)	0.001	Duration of each time slot
num_slots	Derived (T / ΔT)	Total number of time slots
λ_1	10	Average number of active users per slot
num_mini_slots	14	Number of mini-slots in a slot
μ_1 (mean, std)	2, 3	Mean and standard deviation of bits for type1 users
BW (Hz)	100×10^6	Total bandwidth for 5G Sub-6 GHz

The IoT devices were distributed randomly throughout the 5 km by 5 km urban environment in the simulation. We used a uniform distribution model, where the location of each device was determined by randomly drawing its x and y coordinates from a uniform distribution between 0 and 5 km. This model reflects the unpredictable nature of device placement in a real-world urban setting, without any specific patterns.

A. Optimized UAV Positioning and Clustering

In our simulation, we used clustering techniques, such as K-means, PSO, and GA, to segment the IoT devices into clusters based on their geospatial locations. Each cluster was assigned to a UAV-BS, initially positioned at the cluster's centroid. We adhered to a fixed altitude for the UAV-BSs, chosen for optimal performance within urban settings [13]. However, it should be noted that real-world scenarios might require altitude adjustments depending on various factors like regulations and environmental conditions. Upon comparing the output of the three algorithms, we observed that K-means clustering delivered superior initial placements of the UAVs. This finding was quantified using silhouette score analysis, where the K-means approach surpassed both PSO and GA regarding clustering effectiveness. Fig. 2 graphically presents the final UAV positions obtained from these methods in a 2D perspective, while Fig. 3 provides a 3D visualization of the same data. Scattered points represent IoT device locations, while distinctly marked points correspond to the UAV positions. Consequently, K-means clustering is determined as the most suitable technique for the initial positioning of UAVs in our study, providing a reliable benchmark for further optimization processes.

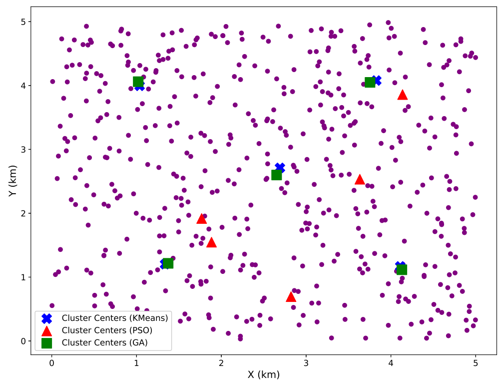

Fig. 2. Comparative representation of UAV positioning (2D) using K-means, PSO, and GA.

B. Robotic CoW Deployment and Network Operations

Fig. 4 delineates our methodical network deployment strategy. Distinctly, the UAV-BSs, depicted as red circles, play a pivotal role by collecting data from IoT devices operating on the 5G NR in the Sub-6GHz spectrum. This spectrum, known for balancing broad coverage with high-speed capabilities, is particularly well-suited for addressing the complexities of IoT communications in urban terrains. After the initial data acquisition phase, optimization algorithms, namely GA and PSO, were deployed to determine the most advantageous positioning for the Robotic CoWs. A significant feature of our network design, these CoWs,

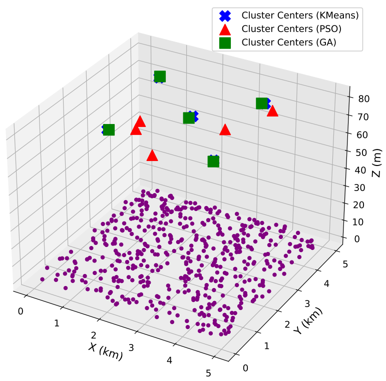

Fig. 3. Comparative representation of UAV positioning (3D) using K-means, PSO, and GA.

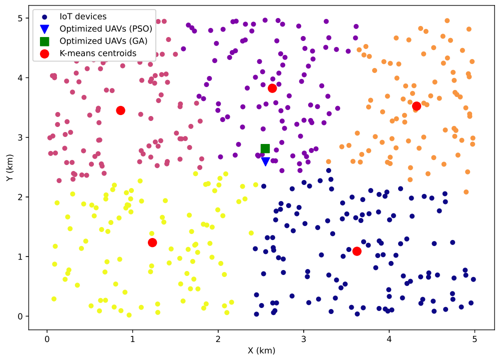

Fig. 4. Deployment of a Robotic CoW with a Tethered UAV.

equipped with TUAVs, serve dual functions: recharging UAVs and offering network backhaul solutions. A side-by-side comparison within the figure reveals the efficacy of GA over PSO in terms of positioning accuracy. In real-time scenarios, the UAVs rely on the 5G NR Sub-6GHz channel to convey the accumulated IoT data to the Robotic CoWs, ensuring a stable, high-throughput connection. Subsequently, the Robotic CoWs dispatch the consolidated data payload to the primary network architecture, realizing an integrated and seamless data pipeline. The graphical representation succinctly visualizes the harmonious interplay between UAVs, IoT modules, and Robotic CoWs in our envisioned network structure. This revised narrative underscores the strategic integration of the 5G NR Sub-6GHz domain for efficient UAV-IoT interactions and situates this technology as a cornerstone for enhancing network proficiency and dependability.

C. Aggregate Data Rate and Total Communication Delay

In our study, we examined how UAV-BSs can help improve network communication by examining two different approaches to data transmission. First, we looked at the traditional method, called 'Normal-slots'. Then, we tried an emerging approach called 'Mini-slots', breaking down each transmission period into smaller parts. Using a graph (see Fig. 5), we found that the 'Mini-slots' approach was consistently better than the traditional method regarding data rate. Digging

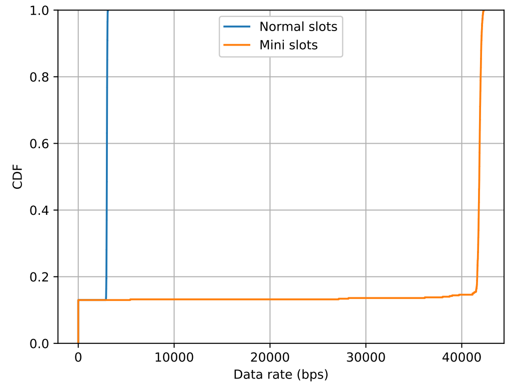

Fig. 5. Graph showing the performance of Normal vs Mini slot methods.

deeper, we also found that the 'Mini-slots' method was quicker because it reduced waiting times, making communications faster overall. We also learned that combining the 'Mini-slots' approach with other modern techniques and using UAVs in smart ways (like for charging) could make networks even more efficient. In short, our study shows that the 'Mini-slots' approach, especially when combined with other modern methods, can be practical for improving communication in urban networks. The graph in Fig. 5 highlights these benefits, pointing to a promising direction for future research and application in cities where fast communication is crucial.

VI. Conclusion and Future Work

In our study, we tackled the optimization challenges of UAV-assisted IoT networks, particularly in urban settings where traditional cellular infrastructures may be compromised. Emphasizing the need for enhanced aggregate data rates and a nuanced understanding of communication delays, we harnessed advanced clustering techniques such as K-means, PSO, and GA. These methods were instrumental in fine-tuning UAV positions, effectively reducing communication distances. Further, integrating Robotic CoWs with TUAVs has significantly augmented our network's robustness and performance, especially in environments with infrastructure vulnerabilities. The 'Mini-slots' scheduling approach emerged as a pivotal strategy, enhancing data throughput while minimizing communication delays. However, it is crucial to clarify that our assessment primarily centred on the repercussions of the 'Mini-slots'. We also recognize the computational demands and system overheads associated with this granular scheduling approach and underscore the need for further investigation.

Exploring diverse clustering algorithms and innovative scheduling paradigms will be paramount as we advance. However, inherent uncertainties and potential errors may persist, like all empirical studies. While we have strived for comprehensive accuracy, real-world IoT deployments' dynamic and complex nature underscores the need for continuous refinement and inquiry. This work is a foundational step, and future endeavours will further optimize UAV-assisted IoT networks within evolving urban landscapes.

References

[1] A. Ali, S. M. Hussain, and G. Begh, "6G and IOT Use Cases," *6G Wireless: The Communication Paradigm Beyond 2030*, vol. 318, p. 315, 2023.

[2] B. Kirubakaran and J. Hosek, "Optimizing Tethered UAV Deployment for On-Demand Connectivity in Disaster Scenarios," in *2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring)*, 2023, pp. 1–6.

[3] Q. Tang, L. Liu, C. Jin, J. Wang, Z. Liao, and Y. Luo, "An uav-assisted mobile edge computing offloading strategy for minimizing energy consumption," *Computer Networks*, vol. 207, p. 108857, 2022.

[4] Y. Zeng, I. Guvenc, R. Zhang, G. Geraci, and D. W. Matolak, *UAV Communications for 5G and Beyond*. John Wiley & Sons, 2020.

[5] Z. Kaleem, W. Khalid, A. Muqaibel, A. A. Nasir, C. Yuen, and G. K. Karagiannidis, "Learning-aided UAV 3D placement and power allocation for sum-capacity enhancement under varying altitudes," *IEEE Communications Letters*, vol. 26, no. 7, pp. 1633–1637, 2022.

[6] I. Jawhar, N. Mohamed, J. Al-Jaroodi, D. P. Agrawal, and S. Zhang, "Communication and networking of uav-based systems: Classification and associated architectures," *Journal of Network and Computer Applications*, vol. 84, pp. 93–108, 2017.

[7] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," *IEEE Access*, vol. 10, pp. 10 031–10 061, 2022.

[8] S. Saafi, O. Vikhrova, G. Fodor, J. Hosek, and S. Andreev, "Cost-and Delay-Efficient Backhaul Selection for Time-Sensitive Maritime Communications," *IEEE Communications Letters*, 2023.

[9] M. A. Kishk, A. Bader, and M.-S. Alouini, "On the 3-D placement of airborne base stations using tethered UAVs," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 5202–5215, 2020.

[10] S. S. Hassan, Y. M. Park, and C. S. Hong, "On-Demand MEC Empowered UAV Deployment for 6G Time-Sensitive Maritime Internet of Things," in *2021 22nd Asia-Pacific Network Operations and Management Symposium (APNOMS)*, 2021, pp. 386–389.

[11] J. Zhang, X. Liu, M. Liang, H. Yu, and Y. Ji, "Low latency dwba scheme for mini-slot based 5g new radio in a fixed and mobile converged twdm-pon," *Journal of Lightwave Technology*, vol. 40, no. 1, pp. 3–13, 2022.

[12] G. dos Santos, F. Sass, V. Hugo, G. Sotelo, N. Vilhena, R. Oliveira, A. Pronto, and J. M. Pina, "Optimization Design of a Saturated Iron Core Fault Current Limiter Using a GA and PSO Algorithms Coupled With Finite Element Method," *IEEE Transactions on Applied Superconductivity*, vol. 33, no. 2, pp. 1–11, 2022.

[13] G. Castellanos, M. Deruyck, L. Martens, and W. Joseph, "Performance evaluation of direct-link backhaul for UAV-aided emergency networks," *Sensors*, vol. 19, no. 15, p. 3342, 2019.