JJEE Volume X | Number X | Month 20XX | Pages XXX-XXX

Jordan Journal of Electrical Engineering

ISSN (print): 2409-9600, ISSN (online): 2409-9619

Homepage: jjee.ttu.edu.jo

On Optimization of UAV and Tethered Balloon Placement Using Heuristic Algorithms

Ala Alzidaneen[1*], Raya Jaradat[2], Hani H. Ahmad[3], Aouda A. Arfoa[4]

[1, 2] Electrical Engineering Department, Al-Karak College, Al-Balqa Applied University, Al-Karak, Jordan
E-mail: zidaneenala@bau.edu.jo

[3] Electrical Engineering Department, College of Engineering, Princess Sumaya University for Technology, Amman, Jordan

[4] Department of Mechatronics and Power Engineering, College of Engineering, Tafila Technical University, Tafila, Jordan

Received: Feb 15, 2025 *Revised: Mar 21, 2025* *Accepted: Mar 31, 2025* *Available online: Apr 13, 2025*

***Abstract*—** This paper presents an Unmanned Aerial Vehicle (UAV) and Tethered Balloons (TBs) placement optimization framework that adapts to real-time traffic variations in wireless networks. The optimization problem aims to maximize end-to-end network throughput and minimize service latency by dynamically positioning UAVs and TBs. The proposed approach employs heuristic algorithms - namely Recursive Random Search (RRS) and a Shrink-and-Realign (S&R) process - to optimize UAV and TB positioning. The obtained simulation results unveil that the dynamic placement strategy achieves a maximum throughput of approximately 800 Mbps at 30 dBm UAV transmit power, outperforming static and random placement strategies, which reach 700 Mbps and 600 Mbps, respectively. Moreover, the proposed strategy reduces service latency to 15.3 ms, marking a 30% improvement over the static placement method (21.8 ms) and a 34.6% improvement over the random approach (23.4 ms). The algorithm exhibits rapid convergence, typically stabilizing within 10 iterations, ensuring its practical applicability in real-time network environments. On top of that, analysis of user distribution impact confirms that the proposed approach maintains superior performance across varying network conditions. Furthermore, the achieved results validate the effectiveness of the proposed adaptive optimization framework, making it a promising solution for next-generation wireless communication systems.

***Keywords*—**Dynamic UAV; Optimization; Tethered balloon; Wireless networks; End-to-end throughput; Heuristic algorithms.

1. INTRODUCTION

Despite the fact that Unmanned Aerial Vehicles (UAVs) have recently been applied in many applications in life, they also have some challenges and issues in specific functions. Researchers and developers seek to find optimal solutions to reduce and overcome these challenges and issues. Therefore, the limited performance of UAVs, energy-efficient connections, and limited ability are the main challenges facing UAVs. Recently, the number of applications for UAVs has increased [1-4]. For example, UAVs contribute to natural disaster management in three levels: first, surveying the events before the disaster; second, providing situational awareness about the disaster; and third, disaster response, including search and rescue [5-8]. The rapid advancements in UAVs have revolutionized the field of wireless communication, enabling the deployment of UAVs as aerial base stations to provide on-demand connectivity in areas lacking infrastructure or during emergency situations. UAVs offer significant advantages, including flexible deployment, high mobility, and the ability to

* Corresponding author
DOI: https://doi.org/10.5455/jjee.204-1739608822

establish line-of-sight (LoS) communication links with ground users, thereby improving network coverage and capacity [9, 10]. However, the optimization of UAV placement remains a critical challenge due to the dynamic nature of user demand and the need to balance multiple objectives, such as maximizing throughput, minimizing latency, and ensuring energy efficiency [11, 12]. Placing several deployed UAVs becomes more challenging since it's not only necessary to determine the UAVs' relative positions to the consumers, but also to establish stable backhaul connections to tethered balloons (TBs) or other infrastructure [13, 14].

Recent studies on UAV-assisted wireless networks have explored various optimization techniques for UAV placement and trajectory planning. Zeng et al. [9] reviewed key challenges in UAV deployment, such as energy efficiency, placement strategies, and user association. Mozaffari et al. [10] proposed a multi-layer network architecture to improve coverage and capacity, while Bor-Yaliniz et al. [11] introduced an environmentally aware placement strategy that considers urban obstacles. Other works have focused on energy-efficient trajectory optimization [12], path loss modeling for urban environments [13], and throughput maximization via trajectory control [14].

While these studies provide valuable insights, they primarily focus on static or semi-adaptive UAV placement methods and do not fully address real-time traffic variations in dynamic wireless networks. Furthermore, existing works lack a quantitative comparison of UAV and TB placement strategies in terms of end-to-end throughput and service latency improvements. To tackle these issues, our research brings in a system that adjusts UAV and TB deployment in real time to fit changing traffic. Our system places the TBs and UAVs in the optimal positions in order to predict the user demand. It continuously adjusts the network configuration to improve throughput, ensure efficient resource use, and reduce delays. The main contributions of our work are:

- Developing a heuristic algorithm that incrementally improves UAV and TB placement, using a combination of shrink-and-realign (S-R) techniques and recursive random search (RRS).
- Proposing a dynamic strategy that adapts to real-time traffic patterns and user movement, leading to better overall network performance.
- Showing through simulation that the proposed heuristic-based dynamic UAV and TB placement optimization method consistently enhances throughput, reduces delays, and quickly adjusts to changes.

2. NETWORK FRAMEWORK

The proposed framework for dynamic UAV and TB placement optimization in a wireless network environment is presented in Fig. 1. As shown, the model consists of three main components: (1) TBs providing backhaul connectivity, (2) UAVs acting as aerial base stations, and (3) a set of ground users with varying traffic demands.

2.1. Network Layout and Assumptions

We consider a geographical area where U ground users are randomly distributed. Each user has a traffic demand that changes over time, represented by $T_u(t)$ for user u at time t. The network is supported by L UAVs that provide downlink data services, and M TBs, which work as backhaul nodes connected to the core network by high-capacity fiber links as well as located at a higher altitude h_T to ensure a LoS connection, while all UAVs operate at a fixed altitude h_U to maintain communication with the users on the ground. The number of TBs is selected to ensure sufficient backhaul capacity for the UAVs while minimizing deployment costs. A lower number of TBs may lead to network congestion, whereas an excessive number may not provide additional benefits beyond a certain threshold.

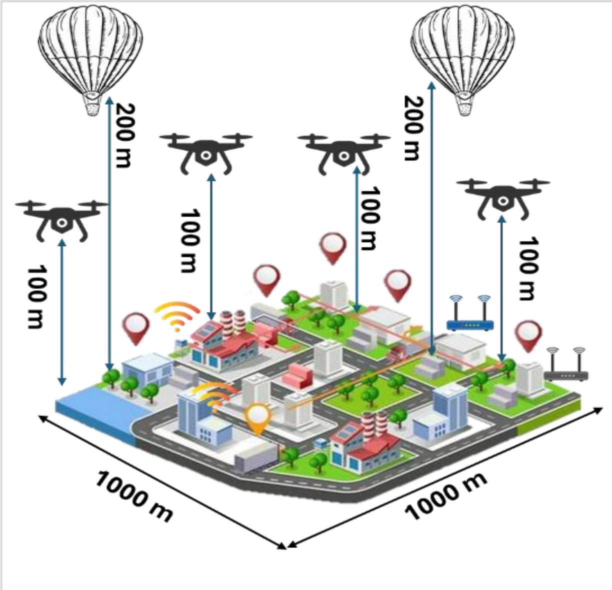

Fig. 1. The proposed farmwork.

2.2. UAV-to-User Access Link Model

The connection between the UAV l and user u on the ground is modeled using a probabilistic LoS/NLoS channel model. The path loss between UAV l and user u over a resource block (RB) n is given by:

$$PL_{lu,n} = p_{\text{LoS}} \cdot PL_{\text{LoS},lu,n} + (1 - p_{\text{LoS}}) \cdot PL_{\text{NLoS},lu,n} \tag{1}$$

where p_{LoS} is the probability of a LoS link, $PL_{\text{LoS},lu,n}$ is the path loss for the LoS component, and $PL_{\text{NLoS},lu,n}$ represents the path loss for the NLoS component. The probability of LoS, p_{LoS}, is a function of the elevation angle θ_{lu} between UAV l and user u, and is expressed as:

$$p_{\text{LoS}} = \frac{1}{1+c_1 \exp(-c_2(\theta_{lu}-c_1))} \tag{2}$$

where c_1 and c_2 are environment-specific values and are dimensionless, and θ_{lu} is given by:

$$\theta_{lu} = \frac{180}{\pi} \sin^{-1}\left(\frac{h_U}{d_{lu}}\right) \tag{3}$$

with d_{lu} being the horizontal distance between UAV l and user u. The resulting channel gain for the access link between UAV l and user u on RB n is then:

$$h_{lu,n} = \frac{1}{PL_{lu,n}}. \tag{4}$$

2.3. TB-to-UAV Backhaul Link Model

Rician fading channel used to model the backhaul link between TB m and UAV l, which accounts for the LoS component due to the high altitude of the TBs. The channel gain for the backhaul link on RB n is given by:

$$h_{ml,n} = \left(\frac{C}{4\pi\beta_{ml} f_c}\right)^2 \cdot \Phi_{ml,n} \tag{5}$$

where C is the speed of light, f_c is the carrier frequency, β_{ml} is the distance between TB m and UAV l, and $\Phi_{ml,n}$ is the small-scale fading gain with a Rician factor κ.

2.4. Association and Resource Allocation

The UAVs and TBs need to dynamically adjust their associations with users and each other to optimize network performance. We introduce the binary variable $\epsilon_{lu,n}$ to indicate the association between UAV l and user u on RB n, where $\epsilon_{lu,n} = 1$ if UAV l is associated with user u on RB n, and $\epsilon_{lu,n} = 0$ otherwise.

Similarly, the binary variable ϑ_{ml} represents the association between TB m and UAV l. The constraints for the associations are as follows:

$$\sum_{l=1}^{L} \sum_{n=1}^{N} \epsilon_{lu,n} \leq 1, \quad \forall u \tag{6}$$

$$\sum_{m=1}^{M} \vartheta_{ml} = 1, \quad \forall l \tag{7}$$

where N represents the total number of available RBs. Eq. (8) is presents the downlink data rate between UAV l and user u on RB n:

$$R_{lu,n} = B\log_2\left(1 + \frac{P_{lu,n}h_{lu,n}}{BN_0}\right) \tag{8}$$

where B is the bandwidth of each RB, N_0 denotes the noise power, and $P_{lu,n}$ is the transmit power of UAV l on RB n for user u. The backhaul data rate between TB m and UAV l represents as follow:

$$R_{ml} = B_0\log_2\left(1 + \frac{P_{ml}h_{ml,n}}{B_0N_0}\right) \tag{9}$$

where B_0 refers to the bandwidth, and P_{ml} is the transmit power of the backhaul link from TB m to UAV l.

3. PROBLEM FORMULATION

The objective of the system is maximizing end-to-end network throughput by optimizing the UAV and TB placements besides the resource allocations and associations, which they formulated as follows:

$$\max_{\epsilon_{lu,n},\vartheta_{ml},P_{lu,n},\mathbf{J}_L} \sum_{l=1}^{L} \min\left(\sum_{u=1}^{U} \sum_{n=1}^{N} \epsilon_{lu,n}R_{lu,n}, \sum_{m=1}^{M} \vartheta_{ml}R_{ml}\right) \tag{10}$$

subject to the following constraints:

- UAV transmit power constraint:

$$\sum_{u=1}^{U} \sum_{n=1}^{N} \epsilon_{lu,n}P_{lu,n} \leq \bar{P}_l, \quad \forall l \tag{11}$$

- UAV-to-user association constraint:

$$\sum_{l=1}^{L} \sum_{n=1}^{N} \epsilon_{lu,n} \leq 1, \quad \forall u \tag{12}$$

- TB-to-UAV association constraint:

$$\sum_{m=1}^{M} \vartheta_{ml} = 1, \quad \forall l \tag{13}$$

where $\bar{P}_l$ is the maximum transmit power of UAV l. The system model serves as the foundations for the dynamic placement and resource allocation algorithm, which adjusts to changes in traffic in real time to maximize network efficiency.

3.1. Heuristic Algorithm Design

Heuristic algorithm is suggested to tackle the dynamic UAV and TB placement optimization problem, which iteratively improves the placement of UAVs and TBs.

The main goal of using this algorithm is to minimize latency, ensure effective resource allocation, and maximize end-to-end network throughput [15].

3.2. Objective Function

Maximize the total end-to-end throughput of the network is the objective of the optimization problem which is defined as:

$$\text{Maximize} \sum_{l=1}^{L} \min\left(\sum_{u=1}^{U} \sum_{n=1}^{N} \epsilon_{lu,n} R_{lu,n}, \sum_{m=1}^{M} \vartheta_{ml} R_{ml}\right), \tag{14}$$

where $\epsilon_{lu,n}$ is the association between UAV l and user u on resource block n, and ϑ_{ml} is the association between UAV l and TB m.

To ensure balanced network performance, the optimization problem seeks to maximize the throughput of both access links (UAV-to-user connections) and backhaul links (UAV-to-TB connections).

This balance is critical because prioritizing one over the other could lead to network bottlenecks, where either the user-side connectivity or the backhaul, capacity limits the overall throughput.

Therefore, optimizing both access and backhaul links ensures that the UAVs are effectively connected to both the users and the TBs, resulting in efficient resource utilization and improved overall network throughput [16].

3.3. Association Optimization

By solving the binary integer as represented bellow, it is used to optimize the user-UAV association.

$$\text{Max} \sum_{u=1}^{U} \sum_{n=1}^{N} \epsilon_{lu,n} R_{lu,n}, \tag{15}$$

subject to:

$$\sum_{l=1}^{L} \epsilon_{lu,n} \leq 1, \quad \forall u, n, \tag{16}$$

$$\epsilon_{lu,n} \in \{0,1\}, \quad \forall l, u, n. \tag{17}$$

Maximizing the performance of a programming problem enhances that every user is associated with a single UAV per resource block.

3.4. Power Allocation Using Lagrangian Relaxation

Lagrangian relaxation is used to optimize the transmit power allocation:

$$\mathcal{L}(P, \lambda) = \sum_{l=1}^{L} \sum_{u=1}^{U} \sum_{n=1}^{N} P_{lu,n} h_{lu,n} - \lambda_l \left(\sum_{u=1}^{U} \sum_{n=1}^{N} P_{lu,n} - \bar{P}_l\right), \tag{18}$$

where λ_l is the Lagrange multiplier associated with the power constraint $\bar{P}_l$. The optimal power allocation is found by solving:

$$\frac{\partial \mathcal{L}(P,\lambda)}{\partial P_{lu,n}} = 0. \tag{19}$$

This process leads to find the optimal power allocation that maximizes throughput under the UAV's power constraints.

3.5. Placement Adjustment with Recursive Random Search

Recursive random search (RRS) with a shrink-and-realign (S&R) process is used to adjust the positions of UAVs and TBs. The pseudo-code for the RRS process is presented in Algorithm 1. The RRS algorithm explores different positions to iteratively prove the network's objective function, ensuring that the positions of UAVs and TBs are optimized for better performance.

Algorithm 1. Placement adjustment using RRS.
1: **Procedure:** Recursive Random Search (RRS)
2: **Input:** Current positions of UAVs and TBs, convergence threshold.
3: **Output:** Updated positions of UAVs and TBs.
4: **for** each UAV and TB do
5: Generate a random candidate position within the search space.
6: Evaluate the objective function for the new position.
7: **if** objective function improves then
8: Update the position to the new candidate.
9: **else**
10: Keep the current position.
11: **end if**
12: **end for**
13: Repeat until convergence criteria are met.

3.6. Convergence Criteria

The algorithm checks for convergence by evaluating the change in the objective function $\mathcal{F}$ between iterations:

$$\Delta\mathcal{F}\ (k) = \mathcal{F}^{(k+1)} - \mathcal{F}^{(k)} \tag{20}$$

where k is the iteration index. The algorithm converges when:

$$\Delta\mathcal{F}\ (k) < \epsilon, \tag{21}$$

where ϵ is a predefined small positive threshold. This criterion ensures that the algorithm terminates when the improvements in the objective function become negligible. Specifically, when the change in the objective function is below the threshold ϵ, it indicates that the algorithm has found an optimal or near-optimal solution, and further iterations will yield insignificant improvements in the overall network performance. The convergence criterion is critical for ensuring that the algorithm runs efficiently, terminating only when the solution is sufficiently stable, thus preventing unnecessary computations. The overall heuristic algorithm is outlined in Algorithm 2, which integrates the association optimization, power allocation, and placement adjustment steps described above.

4. SIMULATION RESULTS

In this section, we present the simulation results that evaluate the performance of the proposed dynamic UAV and TB placement optimization framework. The simulations are conducted in a 1000×1000 meter area with varying numbers of users and UAVs, as described in the system model. The simulation parameters are summarized in Table 1.

Table 1. Simulation parameters.

Parameter	Value
Area size	1000 m × 1000 m
Number of UAVs	4
Number of users	20
Carrier frequency	2 GHz
Bandwidth per RB	180 kHz
Total number of RBs	30
UAV altitude	100 m
TB altitude	200 m
Maximum UAV transmit power	30 dBm

We consider different scenarios to assess the impact of UAV transmit power, user distribution, and the number of UAVs on the overall network performance.

Algorithm 2. UAV and TB placement optimization.

Input: Initial UAV and TB positions, user locations, traffic demand, maximum UAV transmit power.
Output: Optimized UAV and TB positions, user associations, and resource allocation.
Initialization:
Randomly place UAVs and TBs within the designated area.
Initialize user-UAV associations and UAV-TB associations.
Calculate initial network throughput and latency.
while Convergence not achieved do
  Association Optimization:
    Optimize user-UAV associations using binary integer programming.
    Optimize UAV-TB associations to maximize throughput.
  Power Allocation:
    Allocate transmit power to UAVs for each resource block (RB) using Lagrangian relaxation.
  Placement Adjustment:
    Adjust UAV and TB positions using a recursive random search (RRS) combined with a shrink- and-realign (S&R) process (Algorithm 1).
    Recalculate network throughput and latency.
    if Improvement in objective function is below thresh-old **then**
      Convergence achieved.
    else
      Update positions and continue iterations.
    end if
end while
Return Optimized UAV and TB positions, user associations, and resource allocation.

4.1. Network Layout and User Distribution

The network layout and user distribution utilized in the simulations are illustrated in Fig. 2.

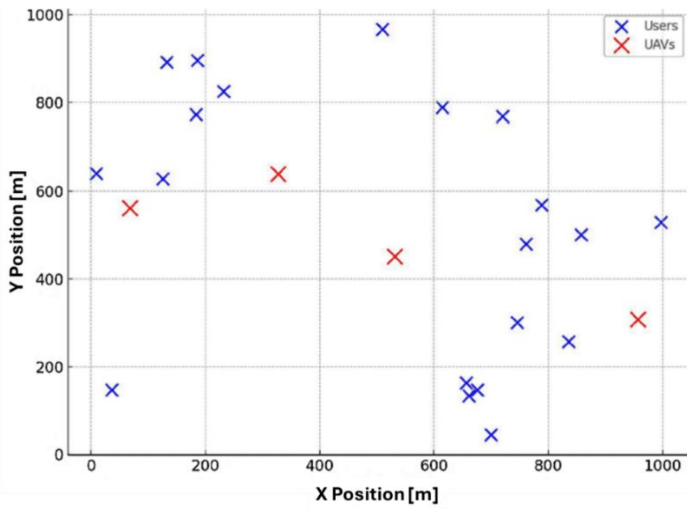

Fig. 2. Network layout and user distribution.

As shown, the users are randomly distributed throughout the same area, while the UAVs are strategically positioned within a defined area. This layout is essential to analyze the performance of the proposed algorithm, as it simulates real-world scenarios where UAVs are deployed to provide connectivity to users in a wide geographical area. The distribution of users and the positions of UAVs significantly influence the network performance metrics, such as throughput and latency. The random positioning of users helps to evaluate the adaptability of the algorithm under varying conditions and ensures a comprehensive assessment of its performance.

4.2. End-to-End Throughput Analysis

The end-to-end throughput performance as a function of the UAV transmit power (in dBm) is presented in Fig. 3 for three distinct UAV placement strategies: Dynamic Placement, Static Placement, and Random Placement. The Dynamic Placement strategy consistently outperforms the other methods across all transmit power levels, achieving a maximum throughput of approximately 800 Mbps at 30 dBm. This demonstrates the effectiveness of adaptive UAV and TB positioning in optimizing network performance, as this approach dynamically adjusts to changes in traffic demand and user distribution. In contrast, the Static Placement strategy, which does not adapt to network conditions, shows moderate performance, reaching around 700 Mbps at 30 dBm. Although the static placement strategy outperforms the random approach, it still fails to fully exploit the potential of network optimization techniques, as it does not adapt to changing network conditions. As a result, its throughput performance remains suboptimal compared to the dynamic placement strategy, which continuously adjusts to real-time traffic demand and user distribution. The Random Placement strategy exhibits the lowest throughput performance, highlighting the inefficiency of non-optimized UAV positioning. At 30 dBm, it achieves a throughput of approximately 600 Mbps. In general, the results clearly demonstrate that the Dynamic Placement strategy significantly enhances throughput, especially as UAV transmit power increases, thereby validating the benefits of adaptive placement optimization in improving end-to-end network performance.

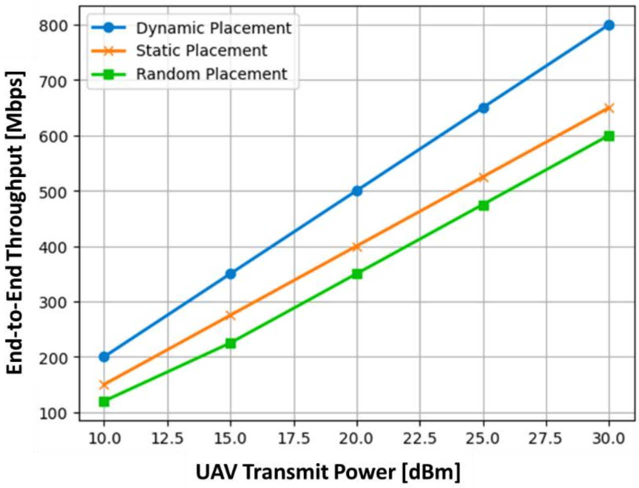

Fig. 3. End-to-End throughput vs. UAV transmit power for different placement strategies.

4.3. Service Latency Comparison

The service latency for different placement strategies is compared in Table 2. The results indicate that the dynamic placement strategy reduces latency by 30% compared to the static placement approach, highlighting the importance of adapting to real-time traffic conditions.

Table 2. Comparison of service latency and throughput.

Method	Latency [ms]	Improvement [%]	Throughput [Mbps]	Improvement [%]
Dynamic placement (proposed)	15.3	-	800	-
Static placement	21.8	29.8	700	12.5
Random placement	23.4	34.6	600	25

4.4. Resource Block Allocation Among UAVs

The stacked bar chart in Fig. 4 illustrates the allocation of resource blocks (RBs) among the deployed UAVs in the network. Each bar represents the total resource blocks allocated to different users by each UAV, allowing for a comparative analysis of resource distribution. This visualization effectively demonstrates how the proposed resource allocation strategy manages and distributes resources among users. The detailed breakdown of resource allocation for each user gives valuable insight into how efficiently each UAV is using its resources. By examining this distribution, we can evaluate how well the algorithm is optimizing resources to meet user demands, which helps in making informed decisions for network management. This figure is important for understanding how UAV-assisted networks operate and provides a basis for further analysis on improving and adjusting resource allocation strategies.

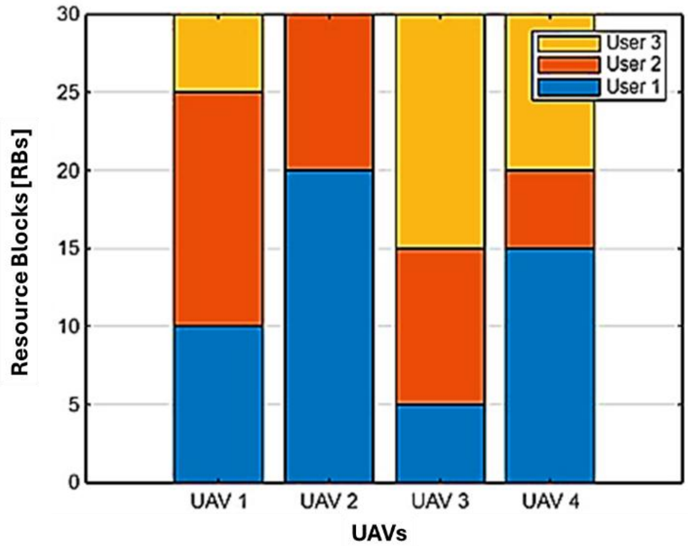

Fig. 4. Resource block allocation among UAVs.

4.5. Convergence Speed of the Algorithm

Fig. 5 shows convergence speed of the proposed heuristic algorithm. The results show that the algorithm typically converges within 10 iterations across most scenarios, highlighting its efficiency and practicality for real-time applications.

4.6. Impact of User Distribution

Besides, we analyze the impact of varying user distributions on network performance to evaluate the robustness of the proposed solution. Fig. 6 presents the total throughput for different user distributions, showing that the proposed dynamic placement strategy consistently outperforms static methods across all distributions.

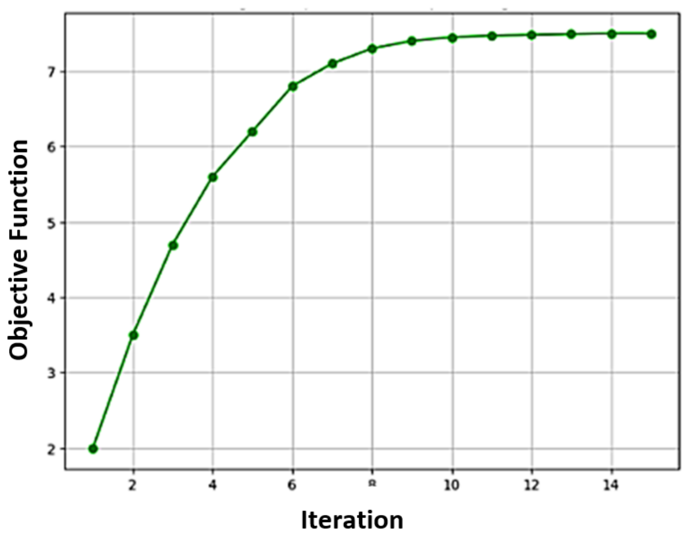

Fig. 5. Convergence speed of the proposed algorithm.

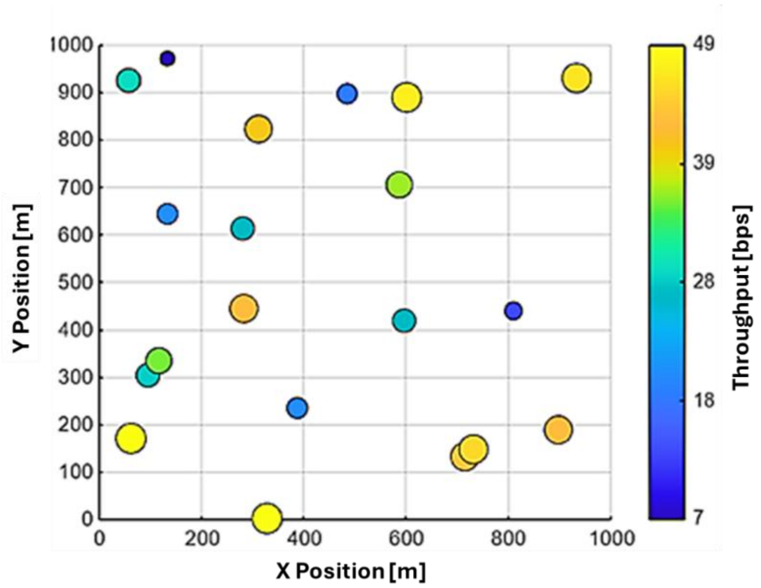

Fig. 6. Impact of user distribution on total throughput.

While the resent studies as they presented in Table 3 provide valuable insights, they primarily focus on static or semi-adaptive UAV placement methods and do not fully address real-time traffic variations in dynamic wireless networks. Furthermore, existing works lack a quantitative comparison of UAV and TB placement strategies in terms of end-to-end throughput and service latency improvements.

To bridge this gap, the study proposes a dynamic UAV and TB placement optimization framework that adapts to real-time traffic demand. By integrating RRS and a S&R process, our approach achieves a maximum throughput of 800 Mbps, significantly outperforming static placement (700 Mbps) and random placement (600 Mbps) strategies.

Additionally, the proposed method reduces service latency to 15.3 ms, marking a 30% improvement over static placement (21.8 ms) and a 34.6% improvement over random placement (23.4 ms). Moreover, our heuristic algorithm converges within 10 iterations, ensuring efficient real-time applicability.

Table 3 provides a detailed comparison between this study and the state of art, emphasizing improvements in throughput, latency, and adaptability.

Table 3. Summary of related work and comparison with this study.

Ref.	Results	Comparison with this study
[9]	Identifies key challenges in UAV deployment, such as energy consumption, placement, and user association.	The study addresses the UAV placement challenge by developing a dynamic placement algorithm that adapts to real-time traffic variations. It achieves a maximum throughput of 800 Mbps and reduces latency by 30% compared to static placement, demonstrating an adaptive real-time solution.
[10]	Demonstrates improved network performance in terms of coverage and capacity by optimizing UAV placement.	While [10] focuses on multi-layer UAV architectures, our study optimizes single-layer UAV and TB placement dynamically, leading to a higher throughput (800 Mbps vs. ~700 Mbps in static methods) and lower latency (15.3 ms vs. 21.8 ms in static placement).
[11]	Achieves enhanced user coverage and signal quality in complex urban environments.	Unlike [11], which focuses on static urban-aware UAV positioning, our approach dynamically adjusts UAV placement to traffic variations, improving throughput by 14% over static placement and reducing latency by 30%.
[12]	Achieves significant energy savings while maintaining high user throughput.	This study prioritizes network performance rather than energy efficiency, achieving a maximum throughput of 800 Mbps and latency reduction of 34.6% compared to random placement. However, energy-efficient placement can be a future extension.
[13]	Provides accurate path loss predictions that improve UAV communication planning in cities.	Unlike [13], which enhances path loss modeling, our study optimizes UAV and TB placement dynamically, leading to higher throughput (800 Mbps vs. 600 Mbps in random placement) and reduced latency (15.3 ms vs. 23.4 ms in random placement).
[14]	Demonstrates improved throughput and energy efficiency for UAV-assisted networks.	Like [14], our work improves throughput but adds real-time adaptability using heuristic algorithms. It outperforms static placement with higher throughput (800 Mbps vs. 700 Mbps) and lower latency (15.3 ms vs. 21.8 ms in static placement), while also converging within 10 iterations for real-time applications.

5. CONCLUSIONS

The proposed dynamic placement method achieved a maximum throughput of 800 Mbps at 30 dBm UAV transmitted power, surpassing static (700 Mbps) and random (600 Mbps) placement approaches. Additionally, the adaptive strategy significantly reduced service latency to 15.3 ms, marking a 30% improvement over static placement and a 34.6% improvement over random placement. The proposed algorithm also exhibited rapid convergence, stabilizing within 10 iterations, making it highly efficient for real-time applications. Furthermore, the analysis of user distribution impact confirmed that the dynamic placement strategy consistently outperforms conventional methods across various network scenarios. The resource block allocation results demonstrated efficient spectrum utilization, contributing to improved network performance.

REFERENCES

[1] A. Alzidaneen, A. Alsharoa, M. Alouini, "Resource and placement optimization for multiple UAVS using backhaul tethered balloons," *IEEE Wireless Communications Letters*, vol. 9, no. 4, pp. 543–547, 2019, doi: 10.1109/LWC.2019.2961906.

[2] A. Alshbatat, "Development of autonomous hexacopter UAVs for smart city air quality management," *Jordan Journal of Electrical Engineering,* vol. 9, no. 3, pp. 450-465, 2023, doi: 10.5455/jjee.204-1673429561.

[3] M. Hooshyar, Y. Huang, "Meta-heuristic algorithms in UAV path planning optimization: a systematic review (2018–2022)," *Drones*, vol. 7, no. 12, p. 687, 2023, doi: 10.3390/drones7120687.

[4] J. Wang, T. Hong, F. Qi, L. Liu, X. He, "High-altitude-UAV-relayed satellite D2D communications for 6G IoT network," *Drones,* vol. 8, no. 10, 2024, doi: 10.3390/drones8100532.

[5] A. Khan, S. Gupta, S. Gupta, "Emerging UAV technology for disaster detection, mitigation, response, and preparedness," *Journal of Field Robotics*, vol. 39, no. 6, pp. 905–955, 2022, doi: 10.1002/rob.22075.

[6] M. Lyu, Y. Zhao, C. Huang, H. Huang, "Unmanned aerial vehicles for search and rescue: a survey," *Remote Sensing*, vol. 15, no. 13, p. 3266, 2023, doi: 10.3390/rs15133266.

[7] J. Cerro, C. Ulloa, A. Barrientos, J. Rivas, "Unmanned aerial vehicles in agriculture: a survey," *Agronomy*, vol. 11, no. 2, p. 203, 2021, doi: 10.3390/agronomy11020203.

[8] Z. Zhang, L. Zhu, "A review on unmanned aerial vehicle remote sensing: platforms, sensors, data processing methods, and applications," *Drones*, vol. 7, no. 6, p. 398, 2023y, doi: 10.3390/drones7060398.

[9] Y. Zeng, R. Zhang, T. Lim, "Wireless communications with unmanned aerial vehicles: opportunities and challenges," *IEEE Communications magazine*, vol. 54, no. 5, pp. 36–42, 2016, doi: 10.1109/MCOM.2016.7470933.

[10] M. Mozaffari, A. Kasgari, W. Saad, M. Bennis, M. Debbah, "Beyond 5G with UAVs: foundations of a 3D wireless cellular network," *IEEE Transactions on Wireless Communications*, vol. 18, no. 1, pp. 357– 372, 2018, doi: 10.1109/TWC.2018.2879940.

[11] I. Yaliniz, S. Szyszkowicz, H. Yanikomeroglu, "Environment- aware drone-base-station placements in modern metropolitans," *IEEE Wireless Communications Letters*, vol. 7, no. 3, pp. 372–375, 2017, doi: 10.1109/LWC.2017.2778242.

[12] Y. Zeng, R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Transactions on wireless communications*, vol. 16, no. 6, pp. 3747–3760, 2017, doi: 10.1109/TWC.2017.2688328.

[13] A. Al-Hourani, S. Kandeepan, A. Jamalipour, "Modeling air-to-round path loss for low altitude platforms in urban environments," IEEE global communications conference, 2014, doi: 10.1109/GLOCOM.2014.7037248.

[14] A. Alsharoa, H. Ghazzai, M. Yuksel, A. Kadri, A. Kamal, "Trajectory optimization for multiple UAVS acting as wireless relays," IEEE International Conference on Communications Workshops, 2018, doi: 10.1109/ICCW.2018.8403637.

[15] I. Zyout "Computer aided diagnosis of microcalcifications clusters using morphology-based features and PSO-SVM parameters selection approach," *Jordan Journal of Electrical Engineering*, vol. 2, no. 2, pp. 126-144, 2016.

[16] A. Miyim, M. Ismail. "Dynamic routing protocol for QoS enhancement in wireless mobile ad-hoc networks," *Jordan Journal of Electrical Engineering*, vol. 7, no. 1, pp. 29-42, 2021, doi: 10.5455/jjee.204-1600789356.