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Coverage and throughput analysis of an energy efficient UAV base station positioning scheme

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ABSTRACT

Recently, the use of unmanned aerial vehicles (UAVs) for wireless communications has attracted much research attention. However, most applications of UAVs for wireless communication provisioning are not feasible as researchers fail to consider some vital aspects of their deployment, especially the energy requirements of both the UAV and communication system. The considerable energy consumption overhead involved in flying or hovering UAVs makes them less appealing for green wireless communications. Therefore, in this work, we examine the feasibility of an alternative energy-efficient deployment scheme where UAVs can be made to land-on designated locations, also known as landing stations (LSs). The idea of LS makes the UAV-based wireless communication more durable and advantageous, since the total energy consumption is reduced by minimizing the flying/hovering energy consumption, which, in turn, enables diverse set of applications including emergency and pop-up networking. We evaluate the impact of the separation distance between these LSs and the Optimal Hovering Position (OHP) on the network performance. Specifically, we develop mathematical frameworks to model the relationship between UAV power consumption, coverage probability, throughput, and separation distance. Numerical results reveal that a significant energy reduction can be achieved when the LS concept is exploited with a slight compromise in coverage probability and throughput. However, the choice of a suitable LS location depends on the users' service requirements, transmit power, and frequency band utilized.

1. Introduction

Unmanned aerial vehicles assisted base stations (UAV-BSs) have been envisioned to play a significant role in 5G and beyond networks including providing an emergency backup network for damaged communication infrastructure during a natural disaster or sudden network failure, data harvesting from the Internet of things (IoT) devices, contents caching for vehicular communication networks. Moreover, they can also be used to provide additional capacity for traffic offloading and load balancing to ease network congestion and improve user throughput, for relaying and coverage extension to connect isolated users to existing cellular networks, and also to enhance the coverage of existing ground networks [1–4]. The major reason for their adoption in wireless communication networks is because of their flexibility, adaptability, easy and quick deployment to the location where their services are needed [5]. However, to realize the full potential of UAVs for providing the aforementioned services in wireless networks there are several challenges and technical issues that need to address such as privacy and public safety concerns, regulation and standardization aspects, limited battery capacity, energy consumption, harsh weather condition, etc [1,6].

Among these challenges, the energy consumption of the UAV-BS happens to be one of the most significant. This is because the UAV has a very limited battery capacity which limits the maximum duration in which the UAV can fly to provide coverage to ground users. According to [4], the maximum flight duration of a small commercial UAV without recharging is about 20–30 mins. This flight duration would further decrease when a base station (BS) is mounted on the UAV to provide coverage to ground users. Hence, to fully exploit the potentials that UAV-BSs provide to cellular networks in terms of additional capacity, coverage extension, and throughput enhancement, their application

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must not result in a significant increase in the total energy consumption of the network. There are already concerns about the energy consumption of UAV-BSs because, in addition to the energy consumed for signal processing and data transmission, there is also the energy consumption due to mobility, which is the most significant component of their energy consumption [5]. Therefore, the energy consumption of UAV-BSs needs to be given special consideration in cellular networks in order to ensure that the gains achieved from their deployment are not overshadowed by the increase in energy consumption.

Various sources of energy have been employed to power UAVs including batteries, fuel cells, renewable energy sources e.g. solar photovoltaic cells and radio frequency-based energy harvesters, etc. For battery-powered miniature UAVs such as rotary-wing UAVs which are commonly used in various domains of wireless communications because of their ability to both hover in a fixed location and well fly across a trajectory, several charging mechanisms have been proposed, including solar charging, laser beam charging, tethering, and wireless power transfer [1,2,7,8]. These charging mechanisms have proven to be quite effective in prolonging the lifespan and service duration of the UAV-BSs without interrupting their service provision as the UAVs do not have to repeatedly go to the charging station to replenish their battery when the energy stored in them depletes. However, despite the advantage of these charging mechanisms, they do not result in a reduction in the energy consumption of the UAV-BSs or the cellular networks where they are deployed. In addition, several energy optimization techniques such as transmission scheduling, power allocation, trajectory design, positioning, etc., have been proposed in the literature [2,4,5] to optimize the energy consumption of UAV-assisted networks. However, these approaches do not result in a significant reduction in the energy consumption of the UAV-BSs, as they still consume a huge amount of energy for hovering and flying, which cannot be sufficiently reduced by these optimization approaches. Therefore, an alternative deployment approach that can significantly reduce the energy consumption due to UAV mobility and hovering must be considered in order to facilitate the adoption of UAVs in a wireless communication network.

An alternative deployment approach to achieving green wireless networks with UAV-BSs is the use of the landing stations (LSs) [9]. LSs are designated spots within the network area such as on top of tall buildings, lamp posts, or specially designed platforms where the UAV-BSs can be made to land to provide coverage to ground users. By adopting the LS approach to UAV-BS deployment, a significant amount of energy can be saved and the service time of the UAV-BS extended because the UAV-BS does not have to continually hover in the air to provide coverage to ground users within a location. In addition, the UAV can use the LSs as stop-over locations along its trajectory to provide service to users, thereby extending its flight time and minimizing its energy consumption [9,10]. Although it might be argued that this approach is similar to a fixed BS deployment, however, this approach is quite different from installing a fixed BS at the LS because the flexibility of the UAV-BS is still maintained, as the UAV-BS only needs to stay at an LS to serve user demands for a specific time and can be redeployed to another location subsequently to meet varying network demands. This is not possible with fixed BSs, thus making the LS more robust and adaptable for wireless network applications. The LS approach, however, has some drawbacks in terms of its practicality. For instance, the pre-designated deployment locations may be an issue because not all the "optimum" deployment options would be possible; it would require permissions from local authorities and/or rental payments. In other words, it will not always be possible to locate the UAV-BS at optimum positions by using the LS approach, which will subsequently affect the coverage and throughput provision.

Accordingly, the authors in [11] introduced a new design of wireless multihop network where they assumed that the BSs can be placed in their optimal locations using UAVs in order to maintain the mesh network. In [9], LSs were utilized to maximize the service time of a UAV-BS and sum-rate of the network. The authors in [12] performed a capacity comparison between hovering and landed mm-wave UAV-BSs in order to enable the selection of the preferred deployment option. However, in the previous works [9,11,12], the optimal locations of the LSs were assumed, while other works on optimal UAV placement without LS [4] consider the UAV-BSs to be constantly hovering to serve user demands, thereby consuming a huge amount of energy. To the best of my knowledge, there are no in-depth studies evaluating the LS positioning vis-a-vis various network performance metrics such as energy consumption, throughput, and coverage probability, which makes this work timely and relevant.

Therefore, in this section, stochastic geometry tools are leveraged to analyze the trade-offs in terms of coverage probability and throughput that can be tolerated when LSs are exploited for UAV-BS deployment to achieve a significant reduction in energy consumption rather than positioning the UAV-BS at the Optimal Hovering Position (OHP). This would assist network operators in finding suitable locations within the network to position the LSs and facilitate the development of new use cases for UAVs in wireless networks. This work is the first attempt at investigating the LS concept from the perspective of determining the suitable locations where they can be positioned within the network to minimize the energy consumption of UAV-BSs while providing the required network performance.

The main focus of this work is on scenarios where a single UAV-BS is deployed to provide back-up services, such as ensuring service continuity during the sudden breakdown of a fixed BS infrastructure or providing capacity enhancement during a sudden surge in traffic demand. In such cases, installing a fixed BS at each LS is not necessary, as the UAV-BS only needs to stay temporarily at one LS before moving to another in response to changing network demand. It is assumed that it is not always possible to coincide an LS and the OHP due to the unavailability of a suitable LS at the OHP.

2. Related works

There are two major techniques of UAVs positioning, they can either be positioned at the OHP which is the popular method adopted in the literature and more recently, the use of LSs to position UAVs is currently been considered. As regards the deployment of the UAV at the OHP, various approaches have been proposed in the literature. Most of the approaches that have been proposed for the optimal positioning of the UAVs try to estimate both the optimal vertical (altitude) and horizontal (2D) location to deploy the UAV, the maximum coverage radius, and the number of UAV required the provide the required Quality of Service (QoS) to ground users. Therefore, in this section, we first review both conventional (analytic and heuristic) and machine learning (ML) approaches that have been proposed in the literature for positioning the UAV-BS at the OHP. Afterwards, we consider the few works that have been proposed on the use of LSs for UAV-BS deployment.

Regarding conventional methods, the authors in [13] investigated the 3D-placement of a UAV-BS to maximize both coverage EE. The problem was formulated as a circle placement problem, after which a heuristic algorithm was developed to estimate the optimal 3D position that enhances the coverage area while ensuring that minimal transmit power is utilized. The work in [14] studied both cost and energy optimization of a UAV-based communication network while considering the energy consumption due to communication and UAV movement. In this regard, a multi-level circle parking (MCP) algorithm was proposed to determine the optimal 3D-hovering positions of the UAVs that would enhance the global EE of the network at both the uplink and downlink. In addition, the results obtained when the proposed algorithm was applied enabled the required number of UAV-BSs to be selected, alongside the determination of the flight parameters required to optimize the overall cost of the system. The authors in [15] introduced a deployment decision mechanism for determining the number of UAV-BSs as well as their respective positions in a UAV-assisted vehicular network to improve the communication coverage and reduce the energy consumption of the UAV-BSs. The proposed strategy leverages circle packing theory to estimate the optimal positions of the UAV-BSs, while an energy optimization model was developed to decrease the power consumption of the UAV-BSs.

The work in [16] introduced an analytic model to estimate the optimal height at which the UAV-BS can be positioned to ensure that the minimum transmit power is utilized while maximizing the coverage provided to a specific area. In [17], the authors proposed an EE maximization strategy for a UAV-BS relay system to prolong the lifetime of the battery while ensuring that the network throughput is maintained. In the proposed mechanism, they considered the hovering position where the UAV-BS utilizes the minimum amount of energy to provide coverage, to be the optimal location for positioning the UAV-BS. This optimal location was first estimated via mathematical analysis, followed by the determination of the optimal power allocation. The work in [18] investigated the optimal placement of a UAV-BS in order to improve its EE while considering as constraints the altitude and minimum data rate of the users. The EE problem was modeled as a monotonic fractional optimization problem after which a polyblock outer approximation algorithm was proposed to solve the problem. Two algorithms for optimizing the location of UAV-BSs were proposed in [19] to reduce the transmission power of the UAV-BS. The first algorithm considers the case where equal power is allocated to all users, while the second algorithm, which is based on successive convex approximation (SCA) does not assume equal power allocation.

The authors in [20] proposed an algorithm for optimal placement of UAV-BSs using Coulomb's law to enhance the EE of the UAV-BSs while the interference between the UAV-BSs and user requirements were considered constraints. The work in [21] considered an energy-aware 3D UAV-BS deployment algorithm using Lagrangian and sub-gradient projection for optimal positioning of the UAV-BSs. In [22], the authors proposed a framework for reducing the energy consumption of each UAV-BS in a multiple UAV-BSs network in the course of performing tasks that are related to the location where they are deployed. The proposed framework employs an order-K Markov predictor to determine the locations where different tasks are performed to ensure that the UAV-BSs are proactively deployed to reduce their energy consumption. In addition, a heuristic algorithm was developed to place the UAV-BSs in their right locations as well as assign their respective tasks to them. The authors in [23] considered the optimal 3D-positioning of a UAV-BS comprising a tilting antenna to enhance the coverage provided to ground users while ensuring that the minimum amount of energy is expended. To achieve optimal positioning, a gradient descent algorithm was developed to determine the optimal height of the UAV-BSs.

In [24], the authors addressed the problem of optimal 3D placement of UAVs while considering the on-board circuit power consumption in order to improve the network lifetime. To achieve this, they employed an analytical method to determine the optimal hovering altitude of the UAV-BSs. Then, using the optimal hovering altitude, the coverage area and on-board circuit power parameters that would result in minimum power consumption were derived. The work in [25] investigated the problem of energy-efficient positioning of UAV-BSs employed for data acquisition from ground users based on non-orthogonal multiple access (NOMA). Then they proposed a heuristic algorithm to estimate the optimal hovering height of the UAV-BS that leads to maximum EE in the network. The work in [26] proposed an optimization scheme that jointly optimizes the 3D location and transmit power of a UAV-based relay network in order to enhance the sum-rate of users. Leveraging alternating descent and SCA, a heuristic algorithm was proposed to tackle the joint optimization problem.

The authors in [27] proposed a joint optimization scheme for both the 3D placement and pathloss factor with the aim of achieving maximum energy-efficient coverage. A heuristic algorithm was developed to find the optimal UAV placement and compensation factor that maximizes energy-efficient coverage. An optimal UAV placement framework that aims to find the optimal UAV locations required to minimize the total energy consumption of the network while providing a target coverage was introduced in [28]. Both centralized and localized heuristic algorithms were developed to determine the optimal UAV locations for both static and mobile users. The authors in [29] considered the joint optimization of the transmission power and location of UAV-BS in a relay NOMA network to minimize the power consumption of the network. A double-loop iterative algorithm was developed to solve the joint optimization problem. In [30], the optimal 3D placement for UAVs serving as relays in IoT communications was considered in order to minimize the transmission power of the UAVs while considering the outage probability of the IoT devices. A 3D placement algorithm based on PSO was developed to minimize the transmitted power in both air-to-ground and ground-to-air links.

The case of energy-efficient UAV placements in indoor environments for emergency wireless coverage was considered in [31]. Both iterative and ES algorithms were developed to determine the optimal position of the UAV in order to minimize the transmission power. Similarly, the authors in [32] investigated the optimal positioning of a UAV-BS for seamless IoT connectivity in an indoor environment comprising multiple users at random locations in order to minimize the transmit power of the UAV-BS. An energy-efficient, low-complexity heuristic algorithm was developed to solve the optimal UAV placement problem. The authors in [33] proposed a UAV-BS deployment and scheduling mechanism to ensure optimal placement and effective management of UAV-BS operations while minimizing energy consumption and ensuring maximum coverage. To achieve these objectives, heuristic algorithms were proposed to ensure the UAVs are placed in the right locations as well as manage their battery recharging cycles.

The authors in [34] investigate EE Maximization in a UAV-assisted NOMA-based network via a joint optimization of UAV placement and power allocation while considering QoS constraints. The joint optimization problem was modeled as a non-linear fractional problem, then an alternating algorithm based on a nested Dinkelbach structure was proposed to find the optimal solution. The work in [35] studied the joint optimization of the UAV location and transmit power in a NOMA-based UAV network while considering the decoding order. The joint optimization problem was first divided into two sub-problems after which an iterative algorithm was proposed to solve the optimization problem alternately. The authors in [36] proposed an energy-efficient transmission mechanism for a UAV-enabled millimeter wave communication system with NOMA by jointly optimizing the UAV position, power allocation, and precoding in order to maximize user coverage and minimize the energy consumption of the UAVs. Due to the complexity of the optimization problem, it was first divided into three sub-problems, and three heuristic algorithms were designed to solve each problem in an iterative manner.

With respect to ML methods, the authors in [37] proposed a proactive power control and positioning framework for UAV-BSs to minimize interference and enhance EE in multi-UAV systems. The proposed framework comprises both offline and online phases. In the former, a supervised learning algorithm (random forest) leverages historical data to build a mobility prediction model, while in the latter, the predicted user positions are exploited to proactively determine the sleep/wake status of the UAV-BSs while an unsupervised ML algorithm (k-means) is employed to update the UAV-BSs positions and regulate the power consumption. An energy-efficient multi-UAV deployment framework was proposed in [38] in order to maximize user coverage probability. An ellipse clustering algorithm was developed to determine the optimal hovering altitude of the UAV that would result in minimal transmit power while maintaining QoS constraints.

A predictive on-demand ML-based UAV deployment for minimizing both the communication and propulsion energy consumption was introduced in [39]. In this regard, an ML framework was developed that uses a Gaussian mixture model (GMM) and weighted expectation Maximization (WEM) algorithm to forecast network traffic congestion areas. Then, k-means algorithm was used to partition the service area of each UAV, after which a gradient-based algorithm was developed to determine the optimal location of the UAVs that results in minimum energy consumption. The authors in [40] considered the problem of reducing the energy consumption required to provide coverage in a multiple UAV network. In pursuit of this objective, a coverage model based on an actor-critic RL algorithm was developed to enhance the cooperation of the UAVs in order to provide energy-efficient coverage.

Although the above-mentioned approaches for positioning the UAV-BS at the OHP can lead to a reduction in the energy consumption of the UAV-BS, however, a significant amount of energy savings cannot be obtained because a huge amount of energy consumption is needed to constantly operate the UAV-BS as the OHP to serve ground users [4,5]. Hence, in order for the UAV-BS to continually serve user requests, there is still a need to further reduce the energy consumption of the UAV-BS using an alternative positioning approach.

An alternative UAV positioning approaches that can greatly reduce the hovering time of the UAV-BSs in order to further enhance the energy savings obtained from the above energy optimization techniques is the use of LSs. The concept of LS was introduced in [9] and it entails positioning the UAV-BS on some designated locations such as the rooftop of tall buildings, lamp posts, or some specially designed platforms that can also be equipped with charging pods, rather than having to hover continuously to serve user requests and expend so much energy, which is a major challenge for battery limited UAVs. This also results in service time and sum-rate maximization.

In this regard, the authors in [12] performed a capacity comparison between landed and hovering UAV with the aim of determining which approach will be suitable for adoption. Their finding reveals that the choice of a suitable deployment option depends on certain factors, including the number of UAVs deployed, the distance between the charging stations and service area, and the capacity of the UAV battery. The work in [10] proposed a deep Q-learning approach for optimizing UAV trajectories using the LS concept, where the UAVs do not have to fly along the trajectory continuously but can land at some locations along its path in order to minimize energy consumption while meeting user demands. However, none of these works considered the optimal location of the LSs in the network, as their position was only assumed. In addition, none of these works have tried to quantify the effect of the relative location of the LS compared to the OHP on key performance metrics such as coverage probability, throughput, and power consumption.

As the use of LS is a relatively new approach compared to the OHP, we argue that more research works need to be done in this direction to determine the optimal locations where UAVs can land along their trajectory and the optimal separation distances between the UAV OHP and the suitable LSs, in order to improve the amount of energy savings while respecting the QoS constraints. Therefore, in this work we employ stochastic geometry tools to evaluate the use of LSs for UAV-BS positioning using various performance metrics including energy consumption, coverage probability, and throughput in order to ascertain their feasibility for enabling green wireless cellular communications. To make it clearer, this work does not propose the LS approach (it has been already in the literature); instead, this work investigates and analyze the potentials and limitations of it in order to showcase its applicability.

2.1. Contributions

This work investigates the impact of the separation distances between the LSs and the OHP on the coverage probability, throughput, and energy consumption of the UAV-BS. The following are the contributions of this work:

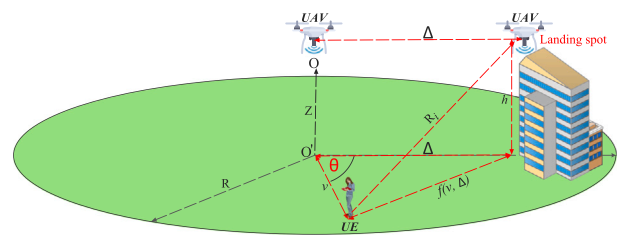


Fig. 1. An illustration of the 3D UAV-BS network.

- Closed-form expressions using stochastic geometry tools are derived to model the relationship between UAV power consumption, coverage probability, throughput, and separation distance.
- The minimum transmit power required to maintain the same QoS at the LS as that of the OHP is derived, and the implication on the power consumption of the UAV-BS is analyzed.
- A comparison of the UAV-BS battery lifetime using the LS approach with that of the OHP approach is performed to highlight the advantage of the LS method.
- The three categories of frequency bands employed in 5G; sub-1 GHz, midband, and mm-wave are considered to investigate the impact of the LS position on the coverage, throughput, and power consumption of the network.
- Numerical analyses are carried out using Monte Carlo simulations to validate the derived analytical models.

3. System model

A 3D UAV network in cylindrical coordinate (r, θ, z) as shown in Fig. 1 is considered. The UAV altitude is assumed to be constant (h), and the coverage area radius is R. The UEs are distributed following a homogeneous Poisson point process (PPP) Φ_u in a 2D plane with density, ϕ_u. The 2D UE distribution can be denoted by $S_u = \bigcup_{x\in\Phi_u} B(O, R)$, where $B(O, R)$ is a 2D circular area with the radius R centered at O. For simplicity and without loss of generality, we have denoted the OHP for deploying UAV-BS as $O \to (0, 0, h)$, and O' is the projection of O to 2D plane. This does not in any way imply that the OHP would always be located at the Origin or center of the environment. The actual OHP is determined based on the location and distribution of the users in the network by following one of the approaches that have been proposed in the literature. However, it is essential to note that this is not the focus of our work. The parameter v is the distance from O' to a typical UE, while θ is the angle formed by the projection of the LS to the 2D plane and the UE. Let the distance between the optimal hovering position O and the LS be denoted by Δ. Then, we define the function $f(v, \Delta) = \sqrt{v^2 + \Delta^2 - 2v\Delta\cos\theta}$ to represent the distance between the UE and a point that is parallel to the LS (meaning the LS projection in the circular plane), and further define R_i as the distance between the LS and UE in 3D space, such that $R_i = \sqrt{h^2 + f(v, \Delta)^2}$. A single UAV deployment scenario is considered, and it is assumed that only the UAV serves the whole area. Hence, the interference is assumed to be negligible.

The channel model consists of the large-scale path loss and the Rayleigh fading component. For a typical UE, its received power from the UAV-BS is

$$P_r = PD_o\left|H_{\mathrm{i}}\right|^2 R_i^{-\alpha}, \tag{1}$$

where P_r is the received power, P is the transmit power, $h_i = \left|H_{\mathrm{i}}\right|^2$, $h_i \sim \exp(\mu)$ is the channel gain and $\mu = 1$, $\alpha > 2$ is the path loss exponent, R_i is the distance between the LS and the ith UE, and D_o is the path

Table 1
UAV-BS power consumption parameters [41,43].

Symbol	Meaning	Value
δ_c	Profile drag coefficient	0.012
ρ	Air density	1.225 kg/m^3
r_s	Rotor solidity	0.4255
R_r	Rotor radius	0.2286 m
A	Rotor disc area	0.1642 m^2
B_v	Blade angular velocity	942.5 rad/s
κ	Incremental correction factor for induced power	0.1
W	Aircraft weight	161.5 Newton
P_o	Circuit power	56 W
η	Amplifier efficiency	2.6
τ_t	Normalized traffic load	1
P	Transmit power	38 dBm

loss at reference distance. We have considered the Rayleigh fading model in this work because it is a commonly used model for multipath interference in wireless communication systems, where the received signal power is assumed to fluctuate randomly due to constructive and destructive interference from multiple paths. Moreover, it is a simple and easily tractable model, making it convenient for theoretical analysis. Additionally, it is assumed that the UAV-BS is equipped with an omnidirectional antenna and that each UE can receive the UAV-BS's signal equally in all directions.

3.1. UAV-BS power consumption

The power consumption of the UAV-BS has two parts: hovering and communication.[1] A rotary-wing UAV is considered in this work because of its ability to hover in a fixed position.

- Power consumption due to hovering of the UAV is [41]:

$$P_{\text{hov}} = \frac{\delta_c}{8}\rho r_s A B_V^3 R_r^3 + (1+\kappa)\frac{W^{2/3}}{\sqrt{2\rho A}}. \tag{2}$$

- Power consumption due to communication is [42,43]:

$$P_{\text{com}} = P_o + \tau_t \eta P. \tag{3}$$

The total power consumption of the UAV-BS, P_{total} can be expressed as the sum of the power consumption due to hovering and that due to communication and is given by:

$$P_{\text{total}} = P_{\text{hov}} + P_{\text{com}}. \tag{4}$$

The parameters in (2) and (3) are defined in Table 1.

It should be noted that even though there are other components of the UAV energy consumption such as that due to UAV communication with the ground station and its movement from one location to another as considered in [44], we have not considered them in this work because we assume that such power consumption is the same for both hovering and LS deployment. This is because, in both deployment scenarios, the UAV-BS still has to move from one hovering position or one LS to another which also requires communication and control from the ground station.

In addition, we assume that the UAV-BS always maintains some amount of energy to reach the required LS. However, in a real network scenario, more than one UAV-BSs would be present in the network and there would also be other charging station in the network asides the one at the LS. As a result, if the battery of a given UAV is not sufficient to reach an LS, it will go to the nearest charging station for recharging while another UAV that has sufficient battery would be deployed to the LS to provide network service.

4. Coverage probability, transmit power, and throughput analysis

In this section, closed-form expressions for finding the coverage probability, minimum transmit power required to maintain the same coverage probability at the OHP using the LS, and the throughput are derived using stochastic geometry. The results obtained from these closed-form expressions are then compared with those obtained using simulations in section 5.5 in order to ascertain their validity.

4.1. Coverage probability analysis

The UAV network is assumed not to receive interference from other BSs. Thus, the coverage probability can be expressed as:

$$\mathrm{P_c}(\lambda) = \mathbb{P}(\Gamma > \lambda), \tag{5}$$

where $\mathrm{P_c}$ is probability that $\Gamma > \lambda$ over the entire circular area with radius R centered at the origin, O. λ represents the minimum threshold value of signal to noise ratio (Γ) that is required for reliable communication.

For a given distance R_i from the UAV position to UE, the Γ is given as

$$\Gamma_i = \frac{D_o\left(\frac{R_0}{R_i}\right)^{\alpha}\cdot (H_i)^2\cdot P}{N}, \tag{6}$$

where D_0 represents the fading power gains from a typical UE to the UAV, R_i is the distance from the UAV location to a typical UE which is given as $R_i = \sqrt{h^2 + \Delta^2 + v^2 - 2\Delta v\cos\theta}$ and N is the system noise, and P is the transmitted power.

Lemma 1. *The downlink coverage probability of the UAV network with the UAVs located at the LSs is given by*

$$\mathrm{P_c} = \frac{1}{2\pi R}\int_0^R\int_0^{2\pi}\exp\left(\frac{-\lambda N}{D_0 P}\times\left[\frac{\sqrt{h^2+v^2+\Delta^2-2\Delta v\cos\theta}}{R_0}\right]^{\alpha}\right)\mathrm{d}\theta\mathrm{d}v. \tag{7}$$

Proof. Inserting (6) into (5), $\mathrm{P_c}$ becomes

$$\begin{aligned}\mathrm{P_c} &= \mathbb{P}\left[\frac{D_o\left(\frac{R_0}{R_i}\right)^{\alpha}\cdot |H_i|^2\cdot P}{N} > \lambda\right]\\ &= \mathbb{P}\left[|H_i|^2 > \frac{\lambda N}{D_0 P}\left(\frac{R_i}{R_0}\right)^{\alpha}\right]\\ &= \mathbb{E}_{r_i}\left[\mathbb{P}\left[|H_i|^2 > \frac{\lambda N}{D_0 p}\left(\frac{R_i}{R_0}\right)^{\alpha}\right]\right]\\ &= \mathbb{E}_{r_i}\left[\exp\left[\frac{\lambda N}{D_0 p}\left(\frac{R_i}{R_0}\right)^{\alpha}\right]\right]\end{aligned} \tag{8}$$

where $h_i = |H_i|^2$ and $h_i \sim \exp(\mu)$ [45]. The coverage probability is obtained over $B(O,R)$ that is defined over $0 \le v \le R$ and $0 \le \theta \le 2\pi$. Note that from Fig. 1 R_i can be expressed as $R_i = \sqrt{h^2 + \Delta^2 + v^2 - 2\Delta v\cos\theta}$. By substituting R_i into (8) and applying integral, the closed-form expression of coverage probability in (7) can be obtained. □

4.2. Transmit power analysis

As the value of Δ increases, the UAV-BS needs to adjust its transmit power in order to maintain the same coverage probability as that of the OHP. To achieve this target, $\mathrm{P_c}[R] = \mathrm{P_c}[R+\Delta]$.

[1] There are other power consumption components, such as processing power consumption, but they are not included in this paper because they are the same in all the comparisons, and therefore they are neglected as they contain insignificant meaning and contribute nothing to the results.

Lemma 2. *The minimum transmit power, P_{ls}, required by the UAV-BS at the LS to maintain the same coverage reliability $\mathbb{P}_c$ at the cell edge as the OHP is given by*

$$P_{\text{ls}} = P\left[1+\frac{\Delta}{R}\right]^{\alpha}. \tag{9}$$

Proof. The coverage probability at cell edge with the aim of meeting the minimum coverage probability of the hovering scenario is given by:

$$\bar{P}_c[R] = \exp\left[\frac{-\lambda N}{D_o P}\left[\frac{R}{R_o}\right]^{\alpha}\right] \tag{10}$$

The minimum transmit power required in LS scenario to maintain the same coverage probability as the hovering scenario is $P_c[R] = \bar{P}_c(R+\Delta)$

$$\exp\left[\frac{-\lambda N}{D_o P}\left[\frac{R}{R_o}\right]^{\alpha}\right] = \exp\left[\frac{-\lambda N}{D_o P_{\text{ls}}}\left[\frac{R+\Delta}{R_o}\right]^{\alpha}\right] \tag{11}$$

let $K = \frac{\lambda N}{D_o R_o^{\alpha}}$

$$\exp\left[-\frac{K}{P}R^{\alpha}\right] = \exp\left[-\frac{K}{P_{\text{ls}}}[R+\Delta]^{\alpha}\right] \tag{12}$$

Hence $P_{\text{ls}} = P\left[\frac{R+\Delta}{R}\right]^{\alpha} = P\left[1+\frac{\Delta}{R}\right]^{\alpha}$ □

Substituting P_{ls} for P in (3), the total power consumption due to communication of the UAV-BS becomes:

$$P_{\text{com}} = P_{\text{o}} + \tau_t \eta P = P_{\text{o}} + \tau_t \eta P\left[1+\frac{\Delta}{R}\right]^{\alpha}. \tag{13}$$

4.3. Throughput analysis

The average throughput can be expressed as $\mathbb{T}_p = B\mathcal{R}/\log 2$, where B is the overall bandwidth of the channel and $\mathcal{R}$, is the average spectral efficiency in nats/s/Hz.

Lemma 3. *The average spectral efficiency of a typical UE in the UAV network with the UAVs located at the LSs is given by*

$$\mathcal{R} = \frac{1}{2\pi R}\int_0^R \int_0^{2\pi}\int_0^{\infty} \exp\left(-\beta^{\alpha/2}\right)\times Q\times\left(e^t-1\right)\mathrm{d}t\mathrm{d}\theta\mathrm{d}v \tag{14}$$

where $\beta = \left(h^2+\Delta^2+v^2-2v\Delta\cos\theta\right)$ and $Q = \frac{N}{D_0 P}\cdot R_0^{-\alpha}$.

Proof. Following [46], the average spectral efficiency can be expressed in terms of the coverage probability as

$$\mathcal{R} \triangleq E_x\left[E_\Gamma[\ln(1+\Gamma)]\right] \tag{15}$$

Given that $E[x] = \int_0^{\infty}\mathbb{P}(x)dx$ for $x > 0$

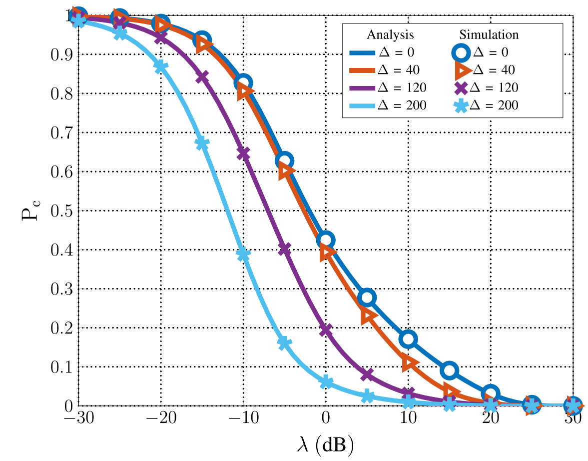
$$\begin{aligned} E_\Gamma[\ln(1+\Gamma)] &= \int_0^{\infty}\mathbb{P}\left[\ln(1+\Gamma) > t\right]\mathrm{d}t \\ &= \int_0^{\infty}\mathbb{P}\left[\Gamma > e^t-1\right]\mathrm{d}t \end{aligned} \tag{16}$$

where $\Gamma = \frac{D_0\left(\frac{R_0}{R_i}\right)^{\alpha}\left[H_i\right]^2\cdot P}{N}$ from (6) and given $Q = \frac{N}{D_0 P}\cdot R_0^{-\alpha}$, $h_i = |H_i|^2$ and hence $\Gamma = \frac{h_k R_i^{-\alpha}}{Q}$. Note that R_i is expressed as $\sqrt{h^2+\Delta^2+v^2-2\Delta v\cos\theta}$

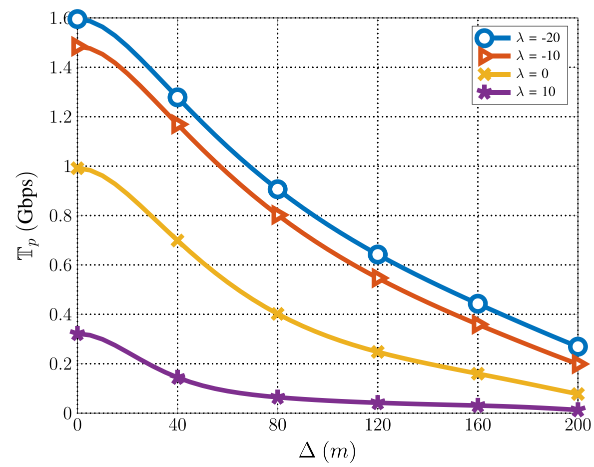
$$E_\Gamma[\ln(1+\Gamma)] = \int_0^{\infty}\mathbb{P}\left[h_k > R_i^{\alpha}Q\left(e^t-1\right)\right]\mathrm{d}t \tag{17}$$

In addition, the probability of random variable h_i can be presented as $\mathbb{P}\left[h_k > R_i^{\alpha}Q\left(e^t-1\right)\right] = \exp\left[-R_i^{\alpha}Q\left(e^t-1\right)\right]$:

$$E_\Gamma[\ln(1+\Gamma)] = \int_0^{\infty}\exp\left(-R_i^{\alpha}Q\left(e^t-1\right)\right)\mathrm{d}t, \tag{18}$$



(a) Coverage probability at 28 GHz



(b) Throughput at 28 GHz

Fig. 2. The coverage probability and average throughput at 28 GHz, for different values of Δ (m) and λ (dB).

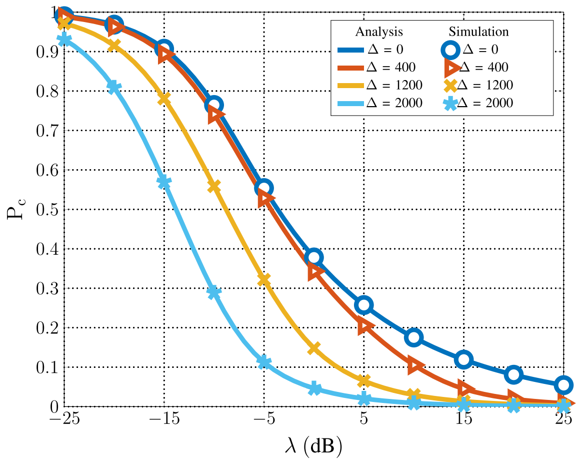
$$\mathcal{R} \triangleq E_{R_i}\left[E_\Gamma[\ln(1+\Gamma)]\right]. \tag{19}$$

By substituting (18) into (19) and integrating over the whole area we obtain the average spectral efficiency expression in (14). □

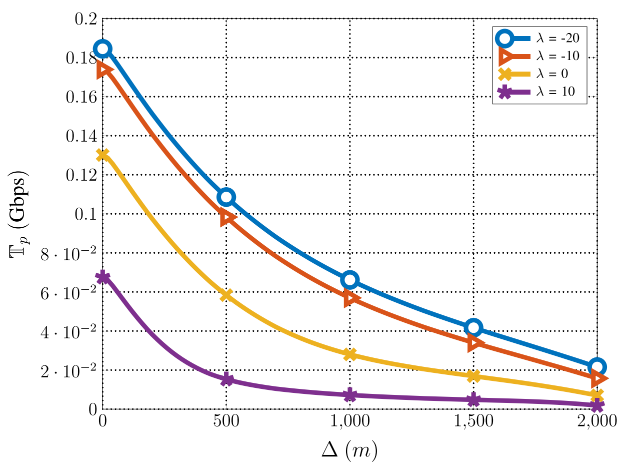
5. Results and discussions

In this Section, the performance of the UAV-BS when deployed at OHP (i.e., $\Delta = 0$) is compared to when deployed at LS and the trade-offs in power consumption, coverage probability and throughput with variations in Δ values are quantified. The analytic formulations are validated in Section 4 using Monte Carlo simulations.

The simulations were carried out for the three categories of frequencies used in the 5G network, namely: sub-1 GHz (750 MHz) with 5 MHz bandwidth, mid-band (3.5 GHz) with 100 MHz bandwidth, and millimeter-wave (mm-wave) (28 GHz) with 1 GHz bandwidth in order to investigate the effect of the LS positioning on the coverage and throughput performance. The number of UEs is set to 300, $\alpha = 3$, h is assumed to be 20 m, $\mu = -174$ dBm/Hz, small-scale fading is taken into account, and an omnidirectional antenna is considered. The area of interest is considered to be a circle with radius $R = 3000$ m, while

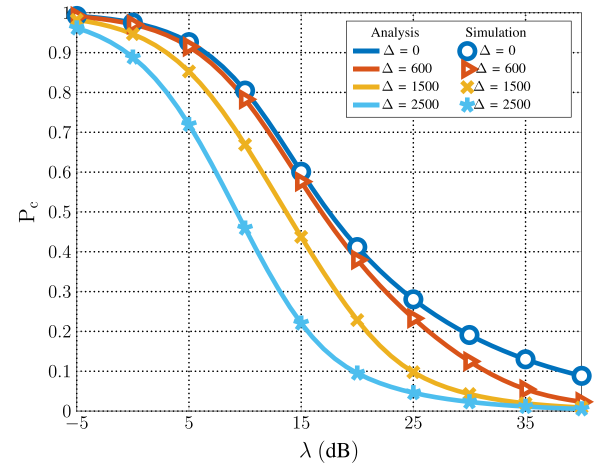


(a) Coverage probability at 3.5 GHz

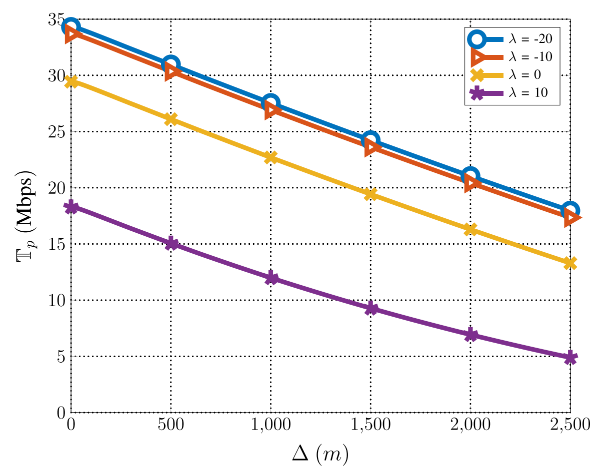


(b) Throughput at 3.5 GHz

Fig. 3. The coverage probability and average throughput at 3.5 GHz, for different values of Δ (m) and λ (dB).



(a) Coverage probability at 750 MHz



(b) Throughput at 750 MHz

Fig. 4. The coverage probability and average throughput at 750 MHz, for different values of Δ (m) and λ (dB).

the UAV-BS is assumed to have maximum coverage radii of 200 m, 2000 m and 3000 m for mm-wave, mid-band and sub-1 GHz bands, respectively. The UAV considered in the simulation is the Aurelia X8 [47], with battery capacity and voltage of 24000 mAh and 22.2 V respectively. The parameters used for both OHP and LS are presented in Table 1. The parameters for the channel model and 5G frequencies were obtained from [48], the BS power consumption parameters were obtained from [42,43] while the UAV power consumption parameters were obtained from [41,47][2] respectively.

It should be noted that we have used an omni-directional antenna for the UAV-BSs as a test case for all the frequency ranges in order to simplify our analysis and ensure uniformity in the comparison of the throughput, coverage probability, and power consumption across all frequency ranges. In the future, we would consider only high frequency and specifically make use of directional antennas which are well suited for such frequencies. In addition, we have selected 20 m as the placement altitude for the UAV-BS in our numerical analysis for the sake of evaluating the proposed models in order to ensure uniformity of comparison across different frequencies for the three performance metrics that are considered in this work. However, the proposed analytical models are adaptable to different altitudes and so can be applied irrespective of the height of the landing station. Therefore, they are suitable for application in real-life UAV-BS deployments.

Table 2
Power consumption comparison of the two types of UAV-BS deployments.

Deployment Type	P_{com} (W)	P_{hov} (W)	P_{total} (W)	Battery life time (min)
OHP	72.38	1335.50	1407.80	22.70
LS	72.38	0.00	72.38	445.65

The power consumption analysis of OHP and LS scenarios with fixed UAV-BS transmit power is shown in Table 2. Table 2 clearly indicates that LS can help increase the battery lifetime by about 20 times that of OHP. While exploiting LSs for UAV-BS deployment could be ideal for energy conservation, the LS might not be at the OHP which could affect network performance in terms of coverage probability and throughput.

[2] It should be noted that in order to make our work realistic, we contacted a UAV manufacturer and also referred to their website to obtain a UAV with a suitable specification that can support the weight of the pico base station that we utilized in this work as some of the parameters used for UAVs power consumption calculations in [41] and other related works are not practicable.

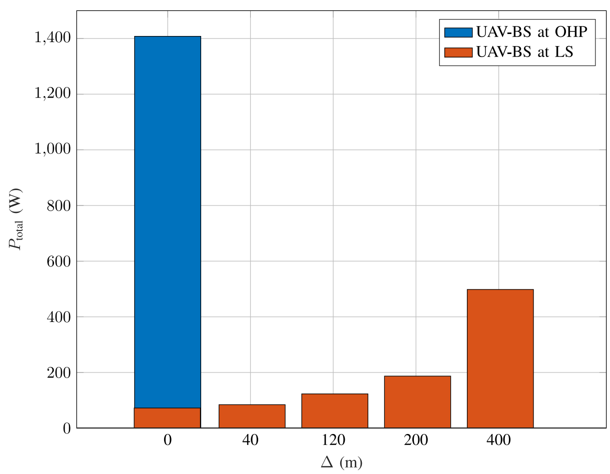


Fig. 5. Total power consumption comparison of the UAV-BS at LS with different values of Δ and the total power consumption of the UAV-BS at OHP. Note that the QoS is maintained despite changes in Δ values for UAV-BS at LS.

The coverage probability at various frequency bands is obtained as shown in Fig. 2(a), Fig. 3(a), and Fig. 4(a), with analytical and simulation results denoted by lines and markers, respectively. It can be seen that the simulation results closely match the analytical curves. Whereas, Figs. 2(b), 3(b), and 4(b) evaluate throughput as a function of Δ for different values of λ. In Fig. 2(a), a very little difference in coverage probability can be observed when the value of Δ is less than 40 m for 28 GHz frequency. However, the difference in coverage probability becomes significant as Δ exceeds 40 m from the OHP. From the throughput perspective, Fig. 2(b) shows there is an exponential decay in the network throughput as the value of Δ increases. This means that moving the UAV-BS away from the OHP would significantly impact system throughput at 28 GHz frequency regardless of the distance of the LS from OHP.

The same analysis is conducted at 3.5 GHz, as shown in Figs. 3(a) and 3(b) for coverage probability and throughput, respectively. A similar trend in the coverage probability and throughput as in Figs. 2(a) and 2(b) is also observed here. However, the value of Δ where only a slight change in the coverage probability is observed, increased from 40 m to 400 m while the throughput is less affected by the shift from the OHP at this frequency compared to the 28 GHz frequency. This means that the LS can be located at a greater distance from the OHP at this frequency band. Figs. 4(a) and 4(b) illustrate the coverage probability and throughput results for the 750 MHz frequency. Fig. 4(a) reveals that the coverage probability at this frequency is least affected by the movement of the UAV-BS away from the OHP. Hence, when the value of Δ is 600 m, the change in coverage probability is very little. The throughput is also least affected at this frequency as a linear decay in the slope of throughput curves is observed as the value of Δ increases for different Γ thresholds. This means that the UAV-BS can be moved farthest away from the OHP without much impact on the performance of the network at this band.

The difference in performance at these frequency bands can be traced to their propagation characteristics. Mm-wave frequency (28 GHz) have a small propagation distance as such, are easily affected by slight movement from the OHP. The 3.5 GHz and 750 MHz frequencies have longer propagation distances, and hence they can tolerate larger values of Δ without much reduction in the network performance.

Finally, as it may not always be possible to locate the LS at the OHP, a suitable position could be at a distance, Δ from the OHP. Hence, the impact on the total power consumption of the UAV-BS due to the increase in Δ is explored while maintaining the same QoS as provided at the OHP. In this regard, the minimum transmits power (P_{ls}) that would be required to maintain the same coverage probability at the cell edge as that of OHP using the LS was first derived in (9). Eq. (9) clearly demonstrates that as Δ increases, the transmit power increases, and that would drive the increase in the total power consumption of the UAV-BS. In Fig. 5, the impact of Δ on the total power consumption of the UAV-BS with LS in comparison to the total power consumption of the UAV-BS with OHP is illustrated. From Fig. 5, it can be clearly observed that the total power consumption of the UAV-BS with LS increases as Δ increases. This increase in the total power consumption is driven by the transmit power increase to maintain the QoS. However, with the increase in the value of Δ from 0 to 400 m, the total power consumption of the UAV-BS with LS at 400 m is still about one-third that of the UAV-BS with OHP.

However, it must be noted that even though it is possible to continue increasing the transmit power in order to maintain the QoS, the extent to which the transmit power can be increased is limited by restriction put in place by regulatory bodies and this ultimately limits the maximum distance that the LS can be situated from the OHP in real network deployments.

6. Conclusion

In this section, the effect of utilizing LSs on UAV energy consumption, coverage probability and throughput performance was investigated. A closed-form expression for each metric was first derived and validated using Monte Carlo simulations. Analytical and simulation results revealed that the distance between the LS and the OHP is inversely related to both the coverage probability and system throughput. However, the magnitude of performance reduction depends on the transmission frequency utilized. It was shown that the performance of the network can be maintained with the LS approach as in the OHP approach by adjusting the transmit power of the UAV-BS. Therefore, network providers can significantly reduce the energy consumption involved in exploiting UAVs for wireless communications by first examining the service requirements of users and the frequency band involved, then the analytical solutions developed in this work can be used to determine the best locations for the LSs as well as the transmit power offset required to maintain the QoS of the UEs.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Attai Abubakar reports financial support was provided by Tertiary Education Trust Fund. Attai Abubakar reports a relationship with University of Glasgow James Watt School of Engineering that includes: employment.

Data availability

No data was used for the research described in the article.

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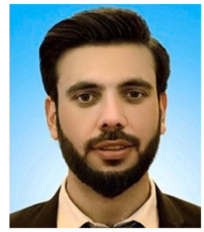

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