Genetic Algorithm-Based Placement and Resource Allocation For Flying Base Stations

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are emerging as key components in next-generation wireless networks, offering adaptable and scalable solutions for dynamic communication environments. However, their effective deployment requires careful optimization of both spatial positioning and resource allocation. This paper addresses the joint problem of three-dimensional placement and transmit power configuration for Flying Base Stations (FBSs) operating in the presence of Macro Base Stations (MBSs). The problem is formulated as a Mixed-Integer Nonlinear Programming (MINLP) task, a class known for its computational intractability. To tackle this complexity, we propose a genetic algorithm-based framework that simultaneously optimizes spatial coordinates, power levels, and activation status for single and multiple FBS scenarios. Unlike conventional approaches that decouple these dimensions or limit their focus to isolated deployments, our methodology integrates spatial positioning, power allocation, multi-FBS coordination, and interference management with MBSs into a unified optimization framework. Simulation results demonstrate that the proposed algorithm achieves near-optimal user coverage and significantly faster convergence compared to a bounded exhaustive search baseline, confirming its effectiveness and scalability in complex deployments involving multiple FBSs and MBSs.**

***Index Terms*—UAV, genetic algorithm, optimization, cellular networks, MINLP.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as key enablers in modern communication networks, enhancing existing paradigms and facilitating the development of novel protocols. Their ability to function as flying base stations (FBSs) provides a flexible and scalable solution for extending network coverage, particularly in remote, disaster-affected, or high-demand areas where traditional infrastructure is limited or infeasible. The increasing commercialization and technological advancements in UAVs have positioned them as key components in next-generation wireless networks, offering improved adaptability, enhanced coverage, and efficient spectrum utilization [1]. Their dynamic repositioning capabilities allow for real-time adjustments in response to fluctuating network demands, making them particularly advantageous in scenarios such as emergency response, large-scale public events, and temporary high-traffic zones [2].

However, despite their potential, integrating FBSs into communication networks presents several challenges. Key constraints include managing bandwidth, transmission power, and flight range, all of which significantly impact the performance and efficiency of FBS deployments [2], [3]. Moreover, the inherent mobility of FBSs introduces complexities in channel modeling, as variations in altitude, trajectory, and environmental conditions can affect signal propagation and reliability. One of the fundamental challenges in FBS deployment is determining the optimal positioning relative to users to ensure the best possible connectivity and coverage. Effective placement must account for multiple factors, including line-of-sight (LoS) probability, non-line-of-sight (NLoS) conditions, interference mitigation, and overall network stability. The optimization of these variables is inherently multi-variate and generally very complex, requiring a careful balance between coverage maximization, latency minimization, power efficiency, and spectral resource management. Furthermore, these challenges are magnified in deployments involving multiple FBSs operating concurrently in the presence of macro base stations (MBSs), where mutual interference and coordination become critical.

To address these challenges, this paper investigates the joint optimization of FBS placement and resource allocation, contributing the following:

- The incorporation of the high-fidelity wireless channel simulator, QuaDRiGa [4], within a comprehensive optimization framework.
- A Genetic Algorithm (GA)-based methodology addressing a rigorously formulated and fully coupled optimization problem encompassing continuous three-dimensional FBS positioning, continuous power allocation, and discrete power state control, scalable to scenarios with multiple FBSs and MBSs.
- A performance comparison conducted against a localized exhaustive search strategy to benchmark optimization efficacy for both single and multi-FBS deployments.

By jointly optimizing the positioning of FBSs across all three spatial dimensions in conjunction with resource allocation, and explicitly extending the methodology to multiple FBSs operating alongside macro base stations, this study introduces a holistic and adaptable framework for enhancing the performance of UAV-assisted communication networks. The proposed methodology leverages GAs to effectively navigate the inherent complexity of this multidimensional optimization problem, illustrating the potential of evolutionary computation in addressing the dynamic and nonlinear characteristics of such systems. The remainder of this paper is structured as follows. Section II reviews related literature on UAV-enabled wireless networks and optimization methods. Section III introduces the system model and key assumptions. Section IV formalizes the optimization problem. Section V describes the proposed genetic algorithm-based solution. Section VI outlines the simulation setup, and Section VII presents and analyzes the results. Finally, Section VIII concludes the paper and suggests directions for future research.

II. Related Work

Several studies have tackled this complex problem from a variety of perspectives. Some have relied on traditional numerical optimization techniques and commercial solvers, while others have adopted heuristic algorithms or machine learning approaches in an effort to find effective solutions. Despite the diversity in methodologies, many of these works share a common foundational setup, particularly in terms of system modeling and performance metrics. In this section, we examine the different approaches in detail, discussing both their points of divergence and convergence.

A. Traditional Approaches

Traditional analytical approaches often reformulate the FBS placement problem to improve tractability. In [5], a probabilistic RF propagation model decomposes user–FBS interaction into LoS and NLoS components, with parameters set by environmental factors such as building density. This enables path loss derivation and reveals a convex relationship between FBS altitude and cell radius, supporting optimal altitude selection.

Extending this, [6] formulates the problem in 3D as a Mixed-Integer Nonlinear Program (MINLP), introducing additional constraints that effectively reduce dimensionality to 2D. The solution employs MOSEK solvers [7] and uses the same propagation model and SINR-based QoS enforcement as [5]. A comparable framework in [8] maintains physical channel modeling and SINR-based QoS, but solves horizontal placement first (via second-order cone programming in MATLAB), followed by altitude optimization.

Although these works enhance tractability via reformulation and dimensionality reduction, such simplifications often rely on assumptions that may not reflect real deployments. Constraints and environmental abstractions, while mathematically convenient, can compromise modeling fidelity and overlook key trade-offs and uncertainties in practical FBS operations.

B. Alternative Methods and Heuristics

Recent works have explored advanced heuristic and learning-based approaches, though many retain similar physical channel modeling assumptions. For instance, [9] employs GAs for 3D FBS placement with users randomly distributed in a bounded area. Horizontal placement is optimized by GA variants, while altitude is handled analytically. The channel models used closely follow those in [5], [6].

A shift toward reinforcement learning is seen in [10], where a Q-learning framework is applied for FBS 3D positioning under diverse QoS requirements. Positional initialization uses k-means clustering, especially for scenarios lacking user location infrastructure, such as post-disaster settings. The probabilistic LoS/NLoS channel model, consistent with earlier studies, allows a balance of tractability and realism and supports rapid experimentation, without any notable additions to physical modeling.

While [9] and [10] address comparable optimization problems, they do so via distinct machine learning paradigms through multi-population GAs and reinforcement learning, respectively highlighting the adaptability of learning-based methods. In [9], FBS height and horizontal positioning are decoupled. [11] similarly uses GAs but assumes a fixed FBS altitude and addresses multiple FBS placements, maintaining these simplifications throughout.

Clustering-based techniques are further illustrated in [12], which applies DBSCAN to find user clusters, then uses KNN-derived centroids to reposition FBSs, though altitude is not optimized and is left for future work.

Overall, while most prior studies decompose the problem for tractability, often preconditioning variables or reducing dimensionality, our approach jointly optimizes all relevant parameters, leveraging a high-fidelity channel simulator and avoiding restrictive assumptions.

III. System and Channel Model

The area being analyzed is an area with U users distributed within it as illustrated in Fig. 1. The distribution of users will be detailed in a subsequent section. Throughout the simulation, multiple FBSs, with the number of FBSs denoted by the term N_{FBS}, are allowed to move freely within the 3D coordinate space, each described by its $(x_{d_n}, y_{d_n}, z_{d_n})$ location vector, where $n = 1, \ldots, N_{\text{FBS}}$. Similarly, the MBS is positioned at fixed coordinates (x_m, y_m, z_m). The location of each user i is denoted by (x_i, y_i).

Each user u_i may receive signals from all FBSs and the MBS present in the environment. For every user, the received power from each base station (whether FBS or MBS) is computed using QuaDRiGa's power map functionality, which produces the received signal strength at each spatial point for a given emitter's configuration. Thus, at any user location, the set of received powers $\{P_{i,b}\}$ is obtained, where b indexes all base stations.

Given the set of received powers, we evaluate the SINR for every user, accounting for all transmitting base stations. Formally, let:

- $P_{u_i,b}$ denote the received signal power at user u_i from base station b (including both FBSs and MBSs),
- $\mathcal{B}$ denote the set of all base stations in the scenario (both FBSs and MBSs),
- N_0 denote the noise power (in mW),
- SINR_{u_i} denote the SINR at user u_i.

Then, the SINR at user u_i served by base station b is computed as:

$$\text{SINR}_{u_i} = \frac{P_{u_i,b}}{\sum\limits_{j \in \mathcal{B},\, j \neq b} P_{u_i,j} + N_0}$$

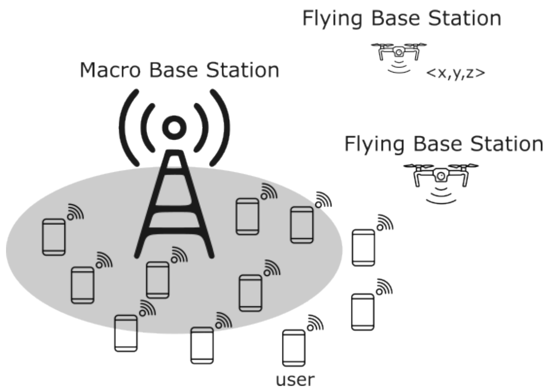

Fig. 1. A representation of the MBS and FBS layout

where the denominator includes the aggregate interference from all other active base stations as well as the noise floor. The user is ultimately associated with the base station providing the highest SINR, subject to a minimum connectivity threshold.

Unlike most works that rely on simplified probabilistic LoS/NLoS models, this study uses QuaDRiGa [4] v2.8.1, a geometry-based stochastic channel simulator, to provide a realistic and detailed wireless propagation environment. QuaDRiGa models 3D multi-cell scenarios with statistical ray tracing, representing environmental effects like buildings and foliage through randomly distributed scattering clusters. It captures key propagation phenomena such as multipath components, mobility-induced drifting, and transitions between environments, and supports dual mobility and satellite-to-ground links, making it highly suitable for dynamic UAV scenarios. Integrating QuaDRiGa enables the evaluation of UAV placement using accurate channel metrics, including path loss and interference, within a realistic simulation setup comprising an MBS and accompanying FBSs.

IV. Problem Formulation

We consider the joint optimization of multiple FBSs, where the objective is to maximize user connectivity, defined by having a specified minimum SINR to achieve a connection, in a bounded area while minimizing interference and power consumption. Each FBS is characterized by its three-dimensional coordinates $(x_{d_n}, y_{d_n}, z_{d_n})$, continuous transmit power p_{d_n}, and activation status variable $s_n \in \{0,1\}$, where $s_n = 1$ indicates that the nth FBS is active and $s_n = 0$ means it is turned off, for $n = 1, \ldots, N_{\mathrm{FBS}}$.

Let $\mathcal{U}$ denote the set of users uniformly distributed in the region of interest. Each user's connectivity is determined by their received SINR, which depends on the locations, transmit powers, and activation statuses of all FBSs, as well as the fixed MBS, together with the environmental propagation characteristics discussed earlier. A user is considered connected if their SINR from any base station (FBS or MBS) exceeds a predefined threshold, i.e., $\mathrm{SINR}_{u_i} \geq \gamma$. The association is made to the base station (FBS or MBS) providing the highest SINR above the threshold.

The optimization objective is to maximize the number of connected users U_{conn}. We express the normalized objective as:

$$\max_{\{x_{d_n}, y_{d_n}, z_{d_n}, p_{d_n}, s_n\}\ ,\ n=1,\ldots,N_{\mathrm{FBS}}} \quad \frac{U_{\mathrm{conn}}}{U} \tag{1}$$

subject to, for each FBS n:

$$x_{d_n} \in [x_d^{\min}, x_d^{\max}] \tag{2}$$
$$y_{d_n} \in [y_d^{\min}, y_d^{\max}] \tag{3}$$
$$z_{d_n} \in [z_d^{\min}, z_d^{\max}] \tag{4}$$
$$p_{d_n} \in [p_d^{\min}, p_d^{\max}] \tag{5}$$
$$s_n \in \{0,1\} \tag{6}$$

Here, $x_d^{\min}$ and $x_d^{\max}$ represent the bounds of the search space for the x-coordinate (similarly for y and z), and $p_d^{\min}$ and $p_d^{\max}$ represent the allowable lower and upper bounds for the FBSs' transmission powers. This formulation enables the simultaneous optimization of spatial placement, power configuration, and activation status for all FBSs, while accounting for their mutual interference and interaction with the MBS. The above formulation is inherently:

- **Non-convex**, due to the SINR function's dependence on distance-based path-loss, complex interference coupling, and the integer nature of the activation variable,
- **NP-hard**, as it involves combinatorial choices of locations, power levels, and activation under interference, making it intractable for traditional solvers.

Given these characteristics, the problem is formulated as a MINLP. Due to the limitations of conventional convex optimization techniques in this context, we adopt an evolutionary approach based on genetic algorithms, which efficiently explores the high-dimensional solution space and yields near-optimal FBS configurations. All variables, including positions, transmit powers, and binary activation states, are jointly processed and optimized.

V. GA-Based Optimization Framework

The optimization is performed using a GA, where each individual encodes all FBSs as a flat vector:

$$\text{Individual} = \big[\, x_{d_1},\, y_{d_1},\, z_{d_1},\, p_{d_1},\, s_{d_1},\, \ldots,\\ x_{d_{N_{FBS}}},\, y_{d_{N_{FBS}}},\, z_{d_{N_{FBS}}},\, p_{d_{N_{FBS}}},\, s_{d_{N_{FBS}}} \big]$$

Each FBS is defined by its 3D coordinates, transmit power, and binary activation status, allowing for joint optimization of all parameters and straightforward scalability to multiple FBSs.

Population Initialization: Initial solutions are sampled uniformly within the feasible parameter bounds. For multi-FBS scenarios, a Matérn hard-core process [13] enforces a minimum separation between FBSs; remaining parameters are independently sampled, and activation status is initialized via Bernoulli sampling.

Crossover and Mutation: Crossover uses a blend operator with crossover probability p_{cr} for continuous variables (position and power), applying a convex combination of parent genes, while binary activation is crossed via a uniform XOR rule. Mutation adds Gaussian noise to continuous variables and randomly flips the activation bit with mutation probability p_{mu}, with all values clamped to feasible ranges.

Selection and Fitness: Parent selection employs tournament selection (size 3), balancing pressure and diversity. Fitness is the ratio of the number of users connected U_{conn} above the SINR threshold and the total users in the space U, encouraging solutions that maximize user connectivity.

Scalability and Runtime: The modular code structure, available at [14], facilitates straightforward extension to scenarios involving multiple FBSs, and can similarly accommodate additional MBSs as needed. All associated attributes for these entities can be adjusted flexibly according to the requirements of each simulation setup.

From a runtime perspective, evolutionary algorithms typically exhibit computational requirements that depend on both the simulation context and the underlying problem structure [15]. Abstracting away the nonlinearities of the physical model, the algorithm's complexity scales approximately linearly with the number of variables (e.g., FBSs) under standard assumptions for problem complexity and search space dimensionality [16]. For a fixed number of genetic iterations, the overall runtime remains polynomial.

VI. Simulation Setup

All simulations are conducted using a MacBook Pro equipped with an Apple M4 Pro processor, 12 CPU cores, and 24 GB of RAM. Parallel computation is utilized to accelerate the evaluation of both the optimization and exhaustive search loops. Propagation modeling is handled using the QuaDRiGa framework with a spatial computation resolution of 1 meter, and all receiver terminals are assumed to be located at a height of 1.5 m above ground level to emulate typical mobile user devices.

The simulation environment consists of 100 users uniformly distributed within a two-dimensional area bounded by $[0, 1500]$ meters in both the x and y directions. A single MBS is placed at a fixed location $(300, 350, 25)$ meters, transmitting at 20 W [17], and its interference is accounted for during all SINR evaluations. The FBS power bounds are defined in Table I [17]. The antenna configuration is defined using QuaDRiGa's modeling tools. All transmitters (MBS and FBSs) are modeled as single-element 3GPP 3D antennas, operating at a center frequency of 2 GHz. The FBS antennas are rotated -90° about the y-axis to align their main lobes horizontally, consistent with aerial deployment. The receiver is modeled as an omnidirectional antenna, emulating a typical mobile device. This antenna configuration is consistently used across both the optimization and exhaustive search simulations.

For generality, the simulation framework is designed to support multiple FBSs, each with independently configurable spatial coordinates, transmission power, and activation status. The optimization thus targets the joint configuration of all FBS locations $(x_{d_n}, y_{d_n}, z_{d_n})$, transmit powers p_{d_n}, and activation statuses s_n for $n = 1, \dots, N_{\text{FBS}}$. The primary performance metric is the number of connected users exceeding a specified SINR threshold of 5 dB [18], regardless of whether connectivity is provided by the MBS or any FBS. Unless otherwise stated, the simulations in this work are performed with a single MBS and a variable number of FBSs to evaluate both single and multi-FBS scenarios. The general simulation parameters are summarized in Table I.

TABLE I
SIMULATION PARAMETERS

Parameter	**Value / Range**	**Symbol**
User Area Size	$[1500, 1500]$ m	–
Number of Users	100	U
Receiver Height	1.5 m	–
SINR Threshold	5 dB	γ
MBS Location	$(300, 350, 25)$ m	x_m, y_m, z_m
MBS Power	20 W	p_m
FBS Horizontal Bounds	$[0, 1500]$ m	$(x_d, y_d)^{\min}, (x_d, y_d)^{\max}$
FBS Altitude Bounds	$[20, 150]$ m	$z_d^{\min}, z_d^{\max}$
FBS Power Bounds	$[7, 10.5]$ W	$p_d^{\min}, p_d^{\max}$
Number of FBSs	Variable	N_{FBS}
FBS Activation	$\{0, 1\}$	s_n
QuaDRiGa Resolution	1 m	–
QuaDRiGa Frequency	2 GHz	–
GA mutation prob.	0.7	p_{mu}
GA Generations	10	–
GA crossover prob.	0.3	p_{cr}
Crossover Alpha	0.5	α
GA Configuration (single/multi)		
GA Population Size	$10, 100$	–
GA mutation scale	$0.199, 0.17$	σ

VII. Simulation and Results

A. Exhaustive Search Baseline

For benchmarking, we perform an exhaustive search over a discretized 3D grid of FBS positions, spanning $x, y \in [300, 1500]$ m in 10 m increments, and altitudes $z \in \{20, 30, 40, 60, 70\}$ m. At each candidate position, the number of users connected above the SINR threshold is calculated with the FBS transmitting at $p_d^{\max}$ and $s_d = 1$.

The maximum observed connectivity is 74 users at 40 m altitude. However, this approach is highly computationally intensive, requiring hours per altitude slice even with parallelization. Table II summarizes the results. The discretization may miss better configurations between grid points, and the search becomes intractable for more than one FBS due to exponential scaling, as illustrated in Fig. 2.

Optimal connectivity regions are generally attained by placing the FBS away from strong MBS coverage regions, since proximity to the MBS increases interference and reduces user association, as shown in Fig. 3. These findings serve as a baseline for assessing the GA's performance and for understanding the impact of FBS parameters on network connectivity.

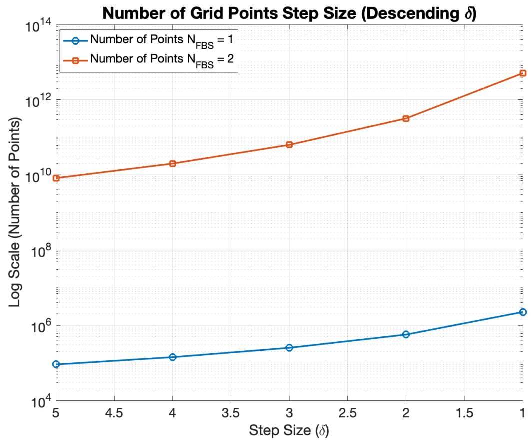

Fig. 2. A plot showing the scaling effect of the exhaustive search considering $N_{\mathrm{FBS}} = 2$ with the difference being several orders of magnitude.

TABLE II
COMPARISON OF EXHAUSTIVE SEARCH AND GA RESULTS

Metric	**Exh.**	**Single GA**	**Multi GA**
Users Connected	74	69	72
Power (W)	10.5	8.95	9.2, 10.1
Time	2.4 hrs/height	20 sec/gen	0.1 hrs/gen

B. Single-FBS GA Results

The GA efficiently solves the joint placement and power optimization over the continuous search space by iteratively refining candidate solutions. Rapid convergence is observed, with individuals typically adopting active status ($s = 1$) and relocating away from MBS-dominated regions within three generations. Altitude and transmit power stabilize at values that jointly maximize connectivity and minimize interference.

The evolution of the fittest individuals is shown in Fig. 3. The GA achieves near-optimal connectivity (69 users, $\sim 6.7\%$ below the exhaustive maximum) with orders-of-magnitude faster computation than exhaustive search (see Table II). Furthermore, the GA identifies solutions at lower altitudes and with reduced transmit power, demonstrating power-aware optimization as illustrated in Fig. 4a.

C. Multi-FBS GA Extension

The GA framework is extended to multi-FBS scenarios, where exhaustive search is impractical. The GA jointly optimizes all FBS positions, altitudes, transmit powers, and activation statuses. Results show notable gains in connectivity and coverage relative to the single-FBS case, as multiple FBSs enable more flexible and efficient user service.

The GA autonomously distributes FBSs to minimize mutual interference and avoid overlaps with MBS coverage, yielding more uniform connectivity and, in some cases, lower overall transmit power. Computation times remain practical, highlighting the method's scalability. Comparative results demonstrate the added value of coordinated FBS operation in terms of both connectivity and resource use. As depicted in Fig. 4b, FBSs collaborate to jointly select optimal heights and powers, while their spatial dynamics are visualized in Fig. 5. The results collectively affirm that while exhaustive search provides a valuable upper bound for single-FBS scenarios, it is the genetic algorithm that offers practical scalability and adaptability to more realistic, multi-FBS wireless network deployments. The GA not only approaches the performance ceiling established by exhaustive search in the single-FBS case, but also scales seamlessly to optimize complex deployments involving multiple flying base stations along with a macro base station. These findings underscore the algorithm's potential for adaptive network planning in next-generation wireless systems.

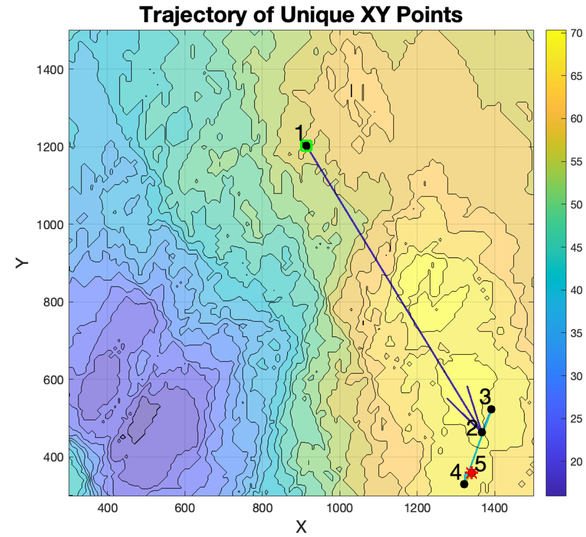

Fig. 3. A 2D section showing the exhaustive planar performance at z_d = 30 and maximal power, with the contour color map representing the obtained number of connected users at each specified FBS placement point. The overlaid trajectory traces the GA's best solutions across generations.

VIII. CONCLUSION

We addressed the joint optimization of 3D placement and power allocation for FBSs coexisting with an MBS, formulating the task as a MINLP and employing the QuaDRiGa channel simulator for realistic wireless environment modeling. All optimization variables were considered jointly. A tailored GA was proposed and benchmarked against exhaustive search. Results show that the GA achieves near-optimal connectivity with dramatically lower computational cost, making it a practical solution for efficient search space exploration. The GA framework also scales efficiently to multi-FBS scenarios, managing added dimensionality and interference. Overall, this work demonstrates the effectiveness and scalability of evolutionary algorithms for adaptive FBS deployment in next-generation wireless networks.

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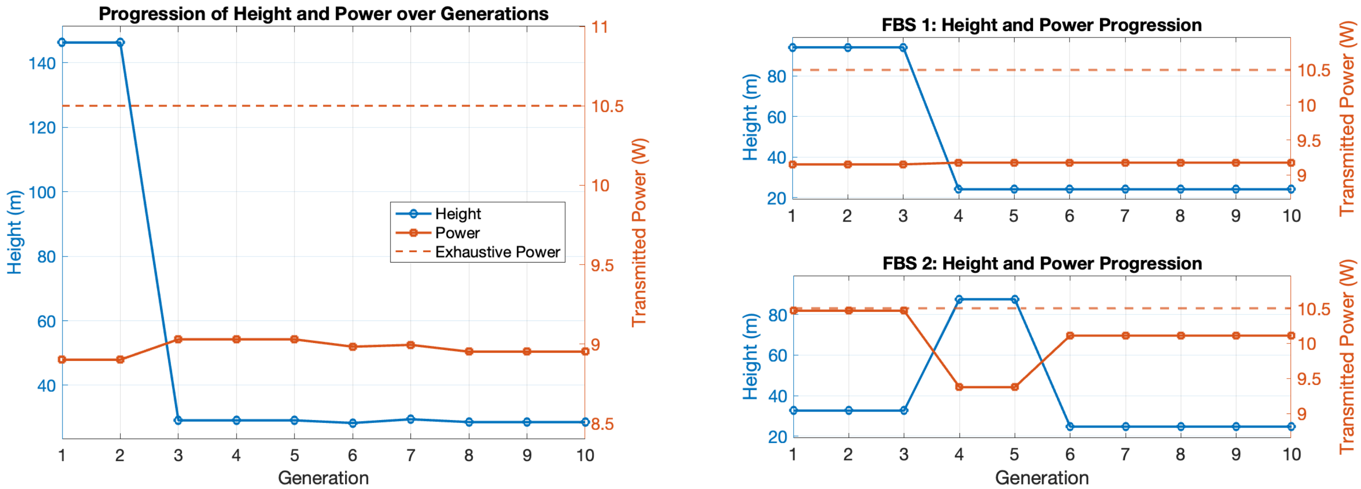

(a) (b)

Fig. 4. (a) Generation index showing progression of FBS altitudes z_d against corresponding transmission powers p_d with a dual axis plot for 1 FBS. (b) Generation index for the same two variables for the multi FBS scenario.

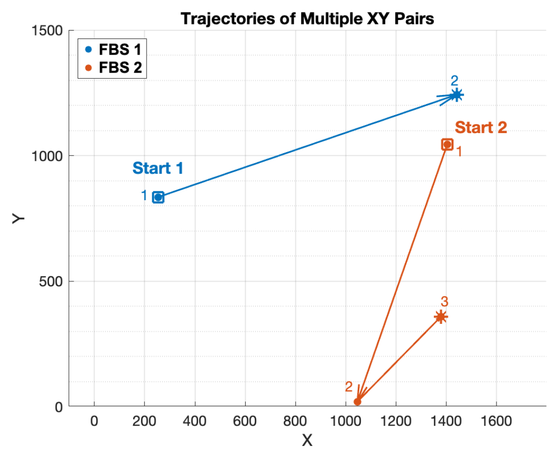

Fig. 5. The chronological progression of planar positioning for both FBSs.

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