Simulation-based Beamforming Optimization in Moving Drones

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***Abstract*— The integration of drone technology with 5G networks presents novel opportunities for enhancing wireless communication systems. This paper explores the application of beamforming optimization techniques in dynamic environments, specifically focusing on moving drones in a simulated environment based on the DeepMIMO O1 scenario. By leveraging the unique properties of the O1 drone setup of DeepMIMO simulation environment, which simulates realistic urban mobility patterns at millimeter-wave (mmWave) frequencies, we propose a novel beamforming algorithm designed to optimize the signal quality and stability in highly mobile aerial networks. Key performance metrics used in this study include Signal-to-Noise Ratio (SNR), battery consumption, and power consumption of both the drones and the base station. Our findings indicate that the adaptive beamforming algorithm not only enhances the SNR and reduces power consumption but also optimizes battery usage compared to conventional beamforming methods. This study enhances the understanding of mmWave beamforming dynamics in aerial scenarios but also lays the groundwork for future advancements in drone-based communication networks.**

Keywords*— *Adaptive Beamforming, 5G Drone Communication, DeepMIMO O1 Scenario, Millimeter-Wave Frequencies, Signal-to-Noise Ratio (SNR) Optimization

I. Introduction

As Unmanned Aerial Vehicles (UAVs), commonly known as drones, become increasingly prevalent in commercial, recreational, and governmental applications, the need for robust and efficient communication systems to support them has become apparent. Particularly, the implementation of 5G technologies offers the potential to dramatically improve the operational capabilities of drones through enhanced data transmission rates, reduced latency, and increased connectivity.

However, the dynamic nature of drones, characterized by high mobility and varying altitudes, poses significant challenges to stable and reliable communication. One promising solution to these challenges is the optimization of beamforming techniques, which can direct the transmission and reception of radio waves to focus on a specific moving target, thereby maximizing the signal quality and efficiency.

Recent research in drone technology and 5G networks have spurred a substantial body of research focused on optimizing communication systems for aerial vehicles. Beamforming, a critical technique for enhancing signal quality and efficiency, has been extensively studied in static and low-mobility scenarios. For instance, traditional beamforming methods often rely on pre-established parameters that do not adapt dynamically to the rapid movements and changing trajectories of drones. Studies have explored fixed beamforming techniques and their application in relatively predictable environments [1][2]. These approaches, while effective in maintaining communication stability in low-mobility contexts, often fall short in dynamic and high-mobility scenarios typical of urban drone operations.

Furthermore, recent advancements have also begun to address the unique challenges posed by highly mobile drones in urban settings. An adaptive beamforming method that leverages machine learning to predict drone movements and adjust beam directions accordingly and a beam alignment algorithm for drone swarms were introduced, emphasizing collaborative signal optimization [3][4][5].

In this paper, we focus on the beamforming challenges and opportunities presented by the DeepMIMO O1 drone scenario [6], a well-regarded dataset that models realistic urban mobility in millimeter-wave (mmWave) frequencies. This scenario provides a perfect testbed to study the effects of beamforming on moving drones, as it includes various user mobility patterns and detailed environmental features. Our main contribution is the development of an adaptive beamforming algorithm that optimizes the directionality and power of beams in real-time as drones move through a simulated urban landscape. We compare our approach to a simpler one (fixed angle beamforming) evaluating metrics such as Signal-to-Noise Ratio (SNR), power consumption of the base station and the drones to demonstrate its effectiveness in maintaining high-quality communication links, thereby ensuring continuous and reliable drone operation as well as better consumption.

Through this study, we aim to push the boundaries of drone communication technology, paving the way for more sophisticated and efficient aerial communication networks in the 5G era and beyond. The paper introduces a beamforming optimization algorithm that stands out from existing research by specifically addressing the rapid mobility and unpredictable trajectory changes of drones in urban environments at mmWave frequencies. Unlike previous studies, which primarily focus on static or predictably moving

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targets, our algorithm dynamically adapts to the real-time movement of drones, leveraging predictive analytics to anticipate future positions and optimize beam directions preemptively, optimizing SNR, the power consumption of the base station while it enhances the drones' signal and the battery consumption of the drones. This proactive approach not only enhances the communication reliability between drones and ground stations but also significantly reduces the latency and overhead associated with re-establishing lost connections due to beam misalignment. Furthermore, the utilization of the DeepMIMO O1 scenario dataset allows for a highly realistic simulation environment that incorporates both the physical and the electromagnetic characteristics of urban landscapes, providing validation for our algorithm that is robust and reflective of real-world operational conditions.

The rest of the paper is organized as follows. Section II discusses the DeepMIMO O1 drone scenario, detailing the environment and its characteristics which provide a realistic testbed for our beamforming optimization algorithm. In Section III, the proposed adaptive beamforming algorithm is introduced, and its implementation is explained. The evaluation metrics are outlined in Section IV, followed by the presentation of the simulation results. Finally, Section V concludes the paper with a summary of the findings and suggestions for future research.

II. DESCRIPTION OF THE ENVIRONMENT

The urban environment of the DeepMIMO O1 drone scenario is characterized by dense building structures, which introduce significant multipath effects. These multipath components are vital in understanding the signal propagation and the resultant beamforming challenges. The scenario includes not only the Line-of-Sight (LoS) paths but also Non-Line-of-Sight (NLoS) conditions, making it a comprehensive testbed for advanced beamforming algorithms. The diverse building heights and materials contribute to varying reflection, diffraction, and scattering effects, which are crucial for realistic simulation outcomes.

The testbed configuration for the DeepMIMO O1 Drone scenario is meticulously designed to emulate a realistic urban environment, providing a challenging setting for evaluating beamforming algorithms. Operating at a frequency of 200 GHz with a transmission power of 45 dBm, the testbed models realistic urban mobility patterns at mmWave frequencies, crucial for high-speed data transmission and low latency.

Across four distinct drone User Grids (UG)—UG1, UG2, UG3, and UG4—a staggering total of nearly 270,000 drones span the skies. These grids, meticulously arranged and vertically aligned, present a mosaic of wireless connectivity challenges. Each grid boasts 124 rows of drones meticulously spaced at 81 centimeters apart and ranging in height from 40 meters to 42.4 meters with each row having 544 drones. At an operating frequency of 200 GHz, the propagation model intricately accounts for reflections, allowing for a nuanced exploration of communication dynamics amidst the urban cacophony.

The drones present in the grids also have velocities from -8m/s to 8m/s and accelerations from $-4m/s^2$ to $4m/s^2$ with the negative values representing the opposite direction from the positive one, chosen at random for each drone so that the predictive beamforming algorithm is able to showcase its superiority over the fixed angles one.

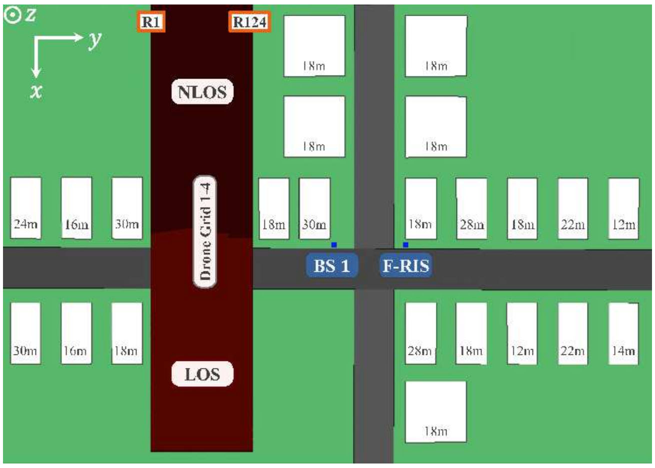

Fig. 1. The top view of the 'O1 Drone' scenario

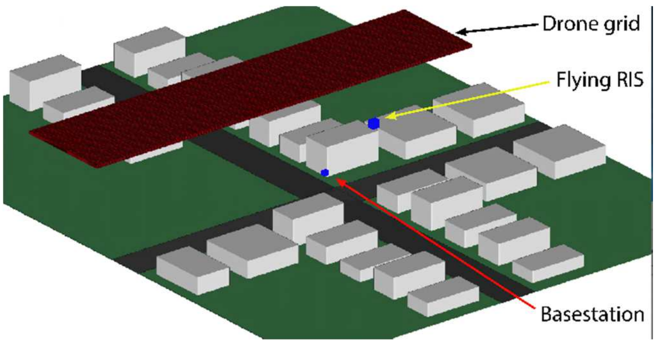

Fig. 2. Bird-eye View of the 'O1 Drone' scenario

As seen in Figure 1 which represents the top view of the environment and in Figure 2 which represents the bird-eye view, two bustling streets intersect, flanked by towering buildings whose heights vary and are prominently displayed. Along the 600-meter-long main street and the 440-meter-long cross street, structures of uniform and varying dimensions define the skyline. Among them, a Base Station (BS1) stands at a modest 6-meter height while a Flying Reconfigurable Intelligent Surface (FRIS) hovers at an elevated 80-meter altitude, strategically positioned approximately 101.86 meters away. The drone grid, illustrated in red, forms a dynamic and flexible infrastructure capable of adjusting its position and orientation to optimize signal transmission and reception. These configurations were chosen to provide a realistic and highly dense drone network, allowing for a nuanced exploration of communication dynamics and the effectiveness of beamforming algorithms.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Main Street Length	600 meters
Cross Street Length	440 meters
Base Station Height (BS1)	6 meters
Drone Grids	UG1, UG2, UG3, UG4
Rows Per Grid	124
Drones Per Row	544
Total Number of Drones	~270,000
Drone Altitude Range	40 - 42.4 meters
Drone Spacing	81 centimeters
Operating Frequency	200 GHz
Transmission Power	45 dBm
Drone Velocity	Randi(-8,8)
Drone Acceleration	Randi(-4,4)

The street setting and the lengths provide a realistic setting that includes both a main and a cross street, simulating typical urban layouts and the base station height represents a typical installation height for urban cellular base stations. As for the drones, the grids represent a dense and structured aerial network. The altitude range and spacing mimic real-world deployment of drone swarms in a controlled formation. These configurations were chosen to model a highly dense and organized drone network. Finally, the transmission power chosen is one that mimics the real-world power of a macro cell base station, and the operating frequency was selected because it falls within the mmWave band, known for its high bandwidth and low latency, which are crucial for high-speed data transmission.

III. ALLOCATION ALGORITHMS

The allocation algorithms in this study are designed to show how the beamforming process can be optimized for moving drones. The DeepMIMO O1 drone scenario will be used only with the BS and without the FRIS. The predictive algorithm that is proposed dynamically adjusts beamforming parameters (azimuth and elevation angles of the beams) to ensure robust and efficient communication links between drones and base stations, considering the high mobility and complex urban environment. The metrics that will be measured include the SNR of the drones, the battery consumption of the drones and the power consumption of both the drones and the base station. A higher SNR value indicates better signal quality, while efficient power usage is critical for base stations and drones when the resources (like the battery life of the drones) are limited. The findings are then compared to the ones that are achieved through having fixed parameters when using the beamforming technique.

The beamforming algorithms employed in this scenario integrate both fixed and predictive beamforming strategies. The fixed beamforming approach maintains a constant beam direction based on the initial positions of the drones. In contrast, the predictive beamforming algorithm dynamically adjusts the beam directions in real-time, leveraging the predicted positions of the drones based on their current velocities and accelerations.

Fixed beamforming is implemented by calculating the initial beam angles (azimuth and elevation) based on the positions of the drones relative to the base station. These angles remain constant throughout the simulation, resulting in a simplified but less adaptive beamforming strategy. The fixed beam angles are determined as follows:

$$Azimuth\_fixed = arctan2((y\_drone - y\_BS)/(x\_drone - x\_BS)) \quad (1)$$

$$Elevationfixed = arctan2(zBS, sqroot((xdrone - xBS)^\wedge 2 + (ydrone - yBS)^\wedge 2)) \quad (2)$$

Equations 1 and 2 calculate the azimuth angle by determining the horizontal angle between the BS and the initial position of the drone and the elevation angle by calculating the vertical angle between the base station and the initial position of the drone for the fixed beamforming strategy. The azimuth angle is the horizontal angle measured from the north direction to the line connecting the base station and the drone. The elevation angle accounts for the difference in height between the base station and the drone, as well as the horizontal distance between them. Both angles remains constant throughout the simulation, making it a simplified approach that does not adapt to the drone's movement [7][8].

Predictive beamforming enhances the communication link by dynamically adjusting the beam directions based on real-time predictions of drone positions. This approach accounts for the drones' velocities and accelerations, ensuring the beams are always aligned with the moving targets. The predictive beam angles are calculated using the predicted positions of the drones:

$$Position\_pred(t) = Position\_current + Velocity \cdot t + 0.5 \cdot Acceleration \cdot t^\wedge 2 \quad (3)$$

$$Azimuth\_pred = arctan2((y\_pred - y\_BS)/(x\_pred - x\_BS)) \quad (4)$$

$$Elevation\_pred = arctan2(z\_BS - z\_pred, sqroot((x\_pred - x\_BS)^\wedge 2 + (y\_pred - y\_BS)^\wedge 2) \quad (5)$$

Equation 3 predicts the future position of the drone at time based on its current position, velocity, and acceleration. By incorporating both the linear and quadratic terms of time, it accurately predicts the drone's trajectory, allowing the beamforming algorithm to preemptively adjust the beam direction. While equations 4 and 5 show the calculation of the predictive azimuth and elevation angles. They both use the predicted x and y coordinates of the drones so this dynamic adjustment can ensure that the beam is accurately aligned with the moving drone and that it accounts fast for changes in horizontal and vertical distance. This method reduces the latency and overhead associated with re-establishing lost connections due to beam misalignment, significantly improving the SNR and power efficiency.

Linear regression played a critical role in our study for modeling the path loss experienced by drones as they moved through the urban environment. By analyzing the data from the DeepMIMO O1 drone scenario, we employed linear regression to establish a relationship between the distance of the drones from the base station and the corresponding path loss. The regression model provided a predictive framework that allowed us to calculate the expected path loss based on the drones' current positions. This approach enabled our beamforming algorithm to dynamically adjust the transmission power and beam direction, thereby optimizing the SNR and ensuring efficient communication. By continuously updating the path loss model with real-time data, the algorithm maintained high signal quality and minimized power consumption, demonstrating the effectiveness of linear regression in enhancing the reliability and performance of drone communication networks [9].

In the simulation code, linear regression is employed to derive the path loss model, which is then used to calculate the path loss for drones at new positions based on their previous positions.

The linear regression model for path loss can be expressed as:

$$Path\ Loss\ (PL) = PL0 + 10\gamma log10(d) \quad (6)$$

Where PL0, γ are constants used and log(d) is a function of the distance between the base station and the drone. The constants PL0 and γ are derived from the linear regression model using the old position data of the drones and then applied so that the new pathloss values are found [10].

The proposed algorithm for beamforming optimization in moving drones leverages predictive analytics to dynamically adjust beamforming angles based on real-time drone movements. Initially, the algorithm loads the DeepMIMO dataset and initializes key parameters such as transmission power and antenna gains. It calculates the Euclidean distance between base stations and drones, derives the path loss model through linear regression and determines fixed beam angles based on initial drone positions. During the simulation, drone positions are updated in each time step considering their velocities and accelerations. Predictive beam angles are then calculated to optimize the SNR and reduce power consumption [11].

Algorithm – Dynamic Beamforming Angles Optimization

```
Function initialize_pathloss_and_snr(dataset, distance_matrix, numUsers):
    initialize pathloss and SNR structures
    for each user (u):
        if pathloss data is available for user:
            store user number, bs index, distance, pathloss, SNR, and user position in structure
    return pathloss and SNR structure

function calculate_fixed_beam_angles(dronePositions, baseStationPosition):
    calculate fixed azimuth and elevation angles for each drone based on initial positions
    return fixedAzimuth, fixedElevation
function simulate_beamforming(numPoints, dt, params, pathloss_and_snr):
    initialize arrays for SNR, power consumption, and battery levels
    calculate fixed beam angles based on initial positions
    for each time step (t):
        update drone positions based on velocities and accelerations
        for each drone (i):
            calculate predictive beam angles
            calculate path loss using log-distance model
            compute SNR for predictive and fixed beamforming
            estimate power consumption based on SNR
            update battery levels
    return results (SNR, power consumption, battery levels)
```

IV. Performance Evaluation

To evaluate the effectiveness of the beamforming algorithms, several performance metrics are considered, including SNR, power consumption of the base station and the battery level/power consumption of the drones. The results from the simulation for 10 randomly selected drones are summarized in Tables II,III, while in Figure 3 and 4 the SNR values of two random drones (with the IDs of 47 and 167) are observed as these drones move through the grid. The blue line represents the SNR that is achieved when the drone is 'hit' with the predictive beamforming angle while the red one represents the SNR values with the fixed angle. In Figure number 3 its power consumption is also observed as it moves closer and then further from the base station it communicates with.

TABLE II. SNR (dB) Comparison for Selected Drones

Drone ID	SNR Fixed (dB)	SNR Predictive (dB)
253	20	45
167	18	40
184	25	50
286	10	20
217	30	50
47	22	35
359	15	30
399	12	20
82	20	30
65	25	40

TABLE III. Base Station and Drones Power Consumptions In Watts

Drone ID	Power Consumption BS Fixed (W)	Power Consumption BS Predictive (W)	Power Consumption Drone Fixed (W)	Power Consumption Drone Predictive (W)
253	350	300	15	10
167	320	310	11	10
184	302	300	10	8
286	350	320	12	11
217	300	290	10	8
47	306	305	10	9
359	320	300	10	8
399	500	490	15	12
82	310	300	10	8
65	305	295	10	8

Table II shows the SNR achieved by these 10 randomly chosen drones when the beamforming was at fixed angles (azimuth and elevation) and the peak SNR achieved by them when the algorithm used position prediction to optimize the angles.

Table III shows the power consumption of the base station when using beamforming on each one of the drones, again with a fixed angle at first and then with the dynamic optimization of the angle.

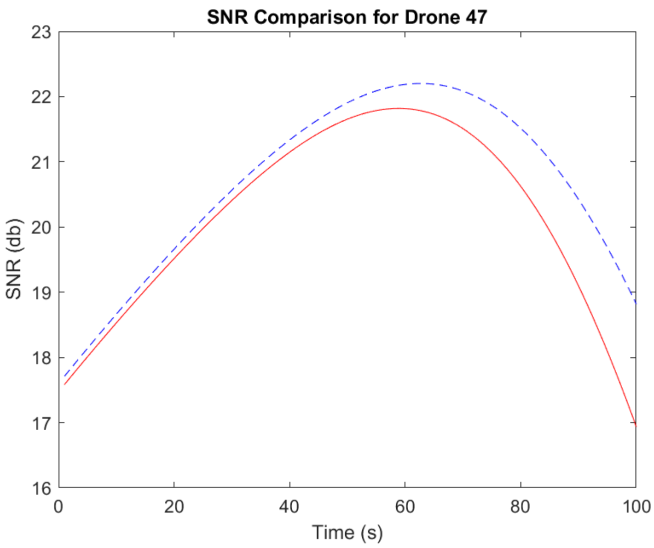

Fig. 3. SNR Result Comparison Of The Two Algorithms For Drone 47

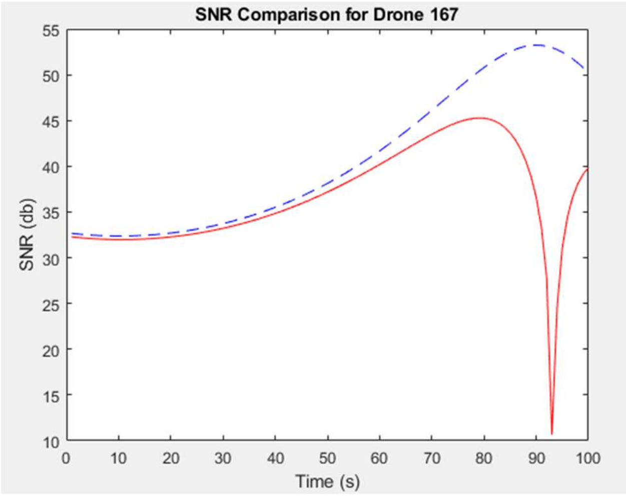

Fig. 4. SNR Result Comparison Of The Two Algorithms For Drone 167

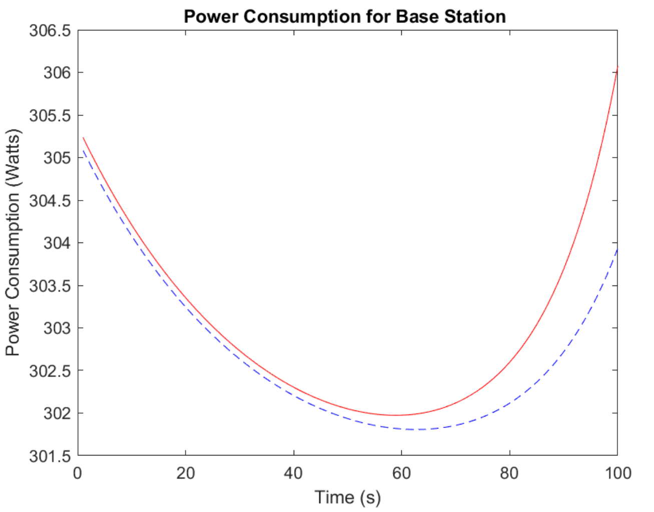

Fig. 5. Power Consumption Of The Base Station During Communication With The Drone 47

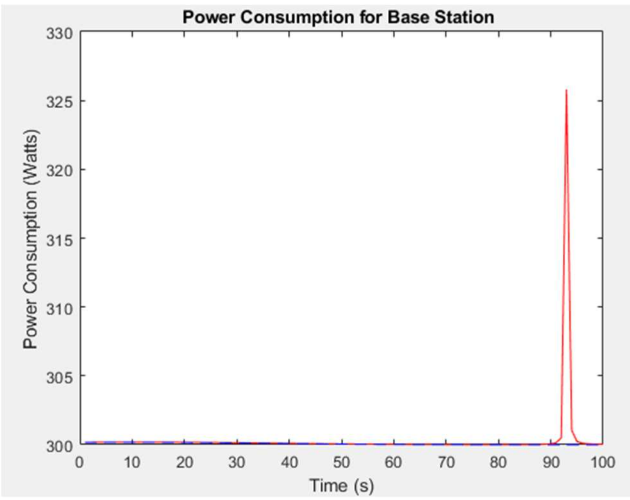

Fig. 6. Power Consumption Of The Base Station During Communication With Drone 167

Figure 3 illustrates how the predictive beamforming algorithm dynamically adjusts the beam direction based on real-time predictions of the drone's position, leading to a significantly higher and more stable SNR. This improvement demonstrates the effectiveness of predictive beamforming in maintaining optimal signal quality by continually aligning the beam with the moving drone, thus reducing signal degradation and improving communication.

The graph in Figure 4 compares the SNR over the 100-second timeframe for drone number 167 which represents a different case than the one of drone 47. The SNR shows a gradual improvement over time, peaking around 50 dB. However, there is a sharp dip around the 90-second mark, where the SNR drops significantly, indicating a moment of poor signal quality. This dip corresponds to the period of LOS loss. Despite the dip, the SNR starts to recover quickly, demonstrating the effectiveness of the predictive algorithm in mitigating the impact of LOS loss. The overall trend in SNR shows the system's resilience and its ability to adapt and recover from signal disruptions, maintaining communication quality as much as possible.

Figure 5 also shows how predictive beamforming results in lower power consumption compared to fixed beamforming, particularly as the drone moves. This reduction is due to the algorithm's ability to preemptively adjust the beam direction, ensuring efficient signal transmission and reducing the need for excessive power to maintain the link and this efficiency is crucial for optimizing the energy usage of both the base station and the drone.

In Figure 6 similar to the drone in Figure 4, the base station's power consumption is relatively stable at around 300 watts for most of the period. However, a dramatic spike occurs near the 90-second mark, with power consumption surging to approximately 325 watts. This spike indicates the base station's response to the drone's loss of LOS, likely ramping up its power output to re-establish a stable connection with the drone. The increased power consumption at the base station highlights the collaborative effort between the drone and the base station to maintain communication despite the disruption.

The simulation results demonstrate that predictive beamforming significantly outperforms fixed beamforming in terms of maintaining higher SNR levels and reducing power consumption. This improvement is attributed to the algorithm's ability to anticipate the movements of drones and adjust beam directions preemptively. The dynamic nature of predictive beamforming ensures that the communication links are consistently optimized, reducing the likelihood of signal degradation due to misaligned beams.

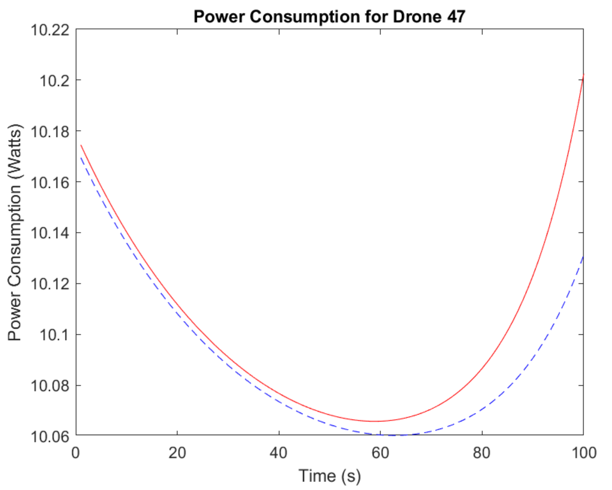

Fig. 7. Power Consumption Of Drone 47 While Communicating With The Base Station

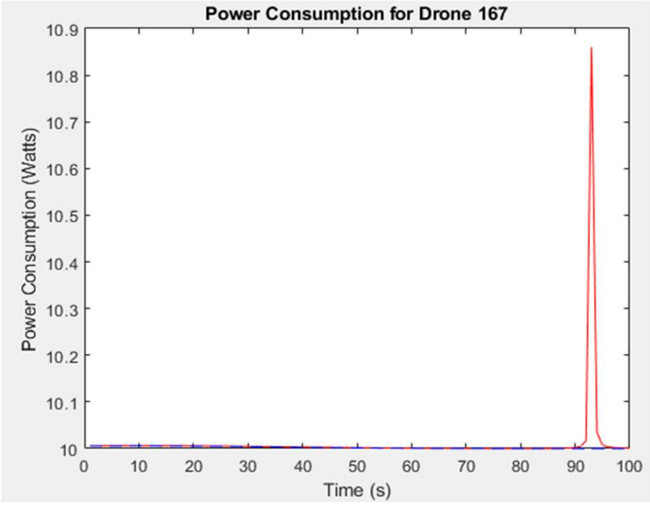

Fig. 8. Power Consumption Of Drone 167 While Communicating With The Base Station

The battery level/power consumption analysis in Figure 7, indicates that while the differences between fixed and predictive beamforming are minimal, the slight improvements in power efficiency can contribute to longer operational times for the drones. This is particularly critical in scenarios where drones are required to operate for extended periods without frequent recharging. And again, in Figure 8 or the majority of the duration, the power consumption remains steady at approximately 10.1 watts and there is a notable spike in power consumption around the 90-second mark, again because of the LOS loss.

V. Conclusion and Future Work

The integration of advanced beamforming techniques with 5G networks represents a pivotal step towards enhancing the operational capabilities of drones, particularly in urban environments. Our study introduces a beamforming optimization algorithm designed to address the rapid mobility and unpredictable trajectory changes characteristic of drones. By leveraging the DeepMIMO O1 drone scenario, we have developed an adaptive beamforming algorithm that optimizes signal quality and stability while reducing latency and power consumption.

The results of our extensive simulations demonstrate the superiority of our predictive beamforming algorithm over traditional fixed approaches. The ability to dynamically adjust beam directions based on real-time predictions of drone positions ensures high-quality communication links and minimizes the likelihood of signal degradation. This advancement is critical for the reliable and efficient operation of drones in urban settings, where maintaining continuous and robust communication is paramount.

Moreover, the slight improvements in power efficiency observed in our simulations can significantly contribute to longer operational times for drones, which is particularly critical in scenarios requiring extended operations without frequent recharging. The ability to maintain high-quality communication with lower power consumption also underscores the practical benefits of our predictive beamforming algorithm in real-world applications.

Our research lays the groundwork for future advancements in drone-based communication networks, highlighting the potential for further exploration into predictive analytics to enhance beamforming techniques. Additionally, expanding the scope of our simulations to include diverse environmental conditions and more complex mobility patterns will provide deeper insights into the practical applications of our algorithm.

In conclusion, our study not only advances the understanding of mmWave beamforming dynamics in aerial scenarios but also establishes a robust framework for the development of future drone-based communication networks. The innovative approach and significant improvements over traditional methods demonstrated by our algorithm pave the way for more reliable, efficient, and resilient drone communication systems in the era of 5G and beyond.

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